MULTIPLE DESCRIPTION PEER-TO-PEER VIDEO STREAMING USING COALITIONAL GAMES

S. Milani, S. Busato, and G. Calvagno

Dept. of Information Engineering, University of Padova,
e-mail: {simone.milani,busatost,calvagno}@dei.unipd.it.

ABSTRACT

Among the recent solutions for Peer-to-Peer video streaming, Multiple Description Coding (MDC) has proved to be an effective solution since it is able to support high flexibility in the network topology and to grant an interruption-free fruition of multimedia contents. However, the presence of losses and congestions on the different links may preclude the reconstruction of the transmitted sequence at the end terminal with a satisfying visual quality. Differentiating the Quality-of-Service levels permits mitigating these inconveniences but requires distributed packet classifications performed by each peer independently. The packet labelling can be modelled via cooperative games where the different uploading nodes are players/descriptions competing for the available network resources. Recent results have shown that cooperative strategies perform better in terms of Quality-of-Experience with respect to non-cooperative and state-of-the-art packet labelling strategies.

1. INTRODUCTION

The streaming of video contents over Peer-To-Peer (P2P) has been an interesting investigation issue for both academic and industrial world. As a natural consequence, research activity has been dedicated worldwide to the development of novel video coding architectures that fit the characteristics of P2P systems.

Some of the proposed solutions rely on a scalable coding, where the input video stream is coded into different hierarchical layers that are uploaded in the network by different peers. The number of uploading peers and the protection levels are adapted according to the significance of packets in the decoding process (i.e., according to the layer they belong to).

A possible alternative is offered by Multiple Description (MD) architectures [1], which have proved to be an effective solution for a continuous and flexible live streaming of multimedia contents (above all for multi-tree P2P networks). MD solutions prove to suit the varying topologies of P2P networks, the heterogeneity of bandwidth availability among the different links, the asymmetry between the uploading and downloading capabilities, and the possible loss of information.

In MD coding (MDC) the original video source is represented by several correlated data streams (descriptions) that are independently coded and transmitted to the receiver over independent channels [2]. In case one or more descriptions are missing because of packet losses or limited bandwidth availability, the correlation that links the different MD streams allows estimating the missing descriptions. Whenever all the descriptions are available at the decoder, the sequence can be reconstructed at full coding quality; in case some data are missing, the visual quality of the reconstructed sequence gracefully degrades. Note that each description is equally important, and as a matter of fact, the quality of the reconstructed sequence depends only on the number and not on the particular subset of correctly-received descriptions. This coding strategy proves to be extremely effective in granting a minimum level of Quality-of-Service (QoS) to the end user since the fruition of the transmitted multimedia content is still possible even with high churning rates and packet losses. As a matter of fact, it proves to be extremely convenient in streaming video contents over P2P networks.

Experimental results have shown that the effectiveness of such approaches varies according to how MD packets are routed and transmitted [3]. Within P2P strategies, several approaches have been proposed to find the optimal topology for the distribution trees of each description. In [4] Wu *et al.* propose a delivery algorithm to maximize the number of descriptions received by the terminal nodes. Other solutions rely on an effective building of multiple delivery trees [5]. It is worth noticing that these approaches imply the election of a controller node that manages the P2P network and finds out the optimal configuration.

Unfortunately, a centralized strategy proves to be ineffective to grant some control over the Quality-of-Service (QoS) level of the different streams. In fact, the central node needs to be updated timely about network conditions and to propagate quickly the required configuration changes to the different peers. This task proves to be quite hard to fulfill since the network could be quite heterogeneous and complex, and as a matter of fact, distributed QoS control algorithms are needed [3].

To this purpose, Game Theory may provide some help in modelling a distributed algorithm to classify MDC packets over a P2P network. Game Theory (GT) has recently proved to be an interesting theoretical framework to analyze and optimize resource allocation problems in digital communication scenarios [6]. Starting from the noncooperative strategy presented in [3], it is possible to improve the performance of the algorithm by allowing a small degree of cooperation between the uploading peers.

In this paper, we present a distributed packet classification strategy based on a coalitional game. Each peer uploads a different description classifying its packets according to the network state (measured by the received RTCP packets, and therefore, related only to its own data path) and the characteristics of the sequence to be transmitted. Within this scenario, we allow couples of peers to communicate among each other exchanging partial information about the network states and agreeing on a joint classification strategy. As a consequence, it is possible to model the distributed classification problem as a cooperative game and schedule the priority of packets analyzing the Nash equilibria. The goal of the player/peer is to minimize the channel distortion affecting his/her own stream and the final reconstructed sequence.

In the following, Section 2 presents the adopted MDC scheme, and describes the problem of packet scheduling for MD coded video. Some basic notions about game theory and the adopted notation are presented in Section 3. Section 4 illustrates the proposed classification strategies which, as simulation results in Section 5 show, provide better results with respect to state-of-the-art solutions. Conclusions are drawn in Section 6.

2. MULTIPLE DESCRIPTION VIDEO STREAMING OVER PEER-TO-PEER NETWORKS

During the last years, several MD video coding schemes have been proposed in literature with different efficiencies and computational complexities. These strategies have proved to be extremely effective for the streaming of video contents over P2P networks. In order

This work was partially supported by the PRIN 2008 project prot. 2008C59JNA founded by the Italian Ministry of University and Research (MIUR).

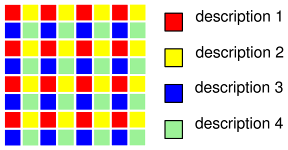


Figure 1: Multiple description coding based on a polyphase subsampling

to test the effectiveness of our classification approach, we considered one of the first MDC schemes based on a polyphase spatial subsampling of the pixels in a frame. The results obtained with this scheme can be easily extended to other MDC approaches.

2.1 MDC based on polyphase subsampling

The MDC scheme we considered operates directly on the input video signal coming from the camera, and it is based on the spatial subsampling of phase-shifted frames of the original video sequence.

The input video frames are subsampled into four subsequences with halved spatial resolution along both dimensions and different phases (see Fig. 1). Each subsequence is then independently coded by an H.264/AVC codec and uploaded in the network by separate repositories (peers or servers). Whenever an end user requires the downloading of the sequence and a delivery network has been defined, each storage terminal starts transmitting the video packets to the destination. In case all the descriptions are received, the coded frame can be reconstructed without any further quality loss. In case some parts or entire descriptions are missing, the MD concealment unit can estimate the lost information via a simple bilinear interpolation. In case all the descriptions have been lost, the missing data are copied from the previously-decoded frame like in most of the Single Description (SD) coding cases, which is less effective than the MDC error concealment.

2.2 MDC packet scheduling in QoS-aware networks

In a network affected by packet losses, it is possible to mitigate the channel distortion produced on the received video signal by ruling the network access according to different QoS classes. Several QoS-aware transmission and network access protocols have been defined ([7, 8]), and their performance strongly depends on how priority classes are assigned to the different packets. The Single-Rate-Three-Colors-Markers (srTCM) approach [8] distributes packets among three classes according to the negotiated average bit rates. However, when transmitting MD streams it is necessary to grant a certain degree of diversity among the loss patterns affecting the different descriptions (*inter-stream* diversity) [9]. In case the congestion affects all the streams, the effectiveness of the MDC error concealment algorithm relies on the fact that at least one description is available at the decoder, and therefore, the probability that all the descriptions are lost has to be minimized by assigning different QoS classes to different streams and varying their relative loss probability (inter-stream diversity). On the other hand, in case the congestion affects a single description, it is necessary to identify those packets that are crucial in the decoding process and to increase the assigned QoS level reducing the loss probability (intra-stream diversity).

As for P2P networks, an optimal configuration can be achieved by electing a controller node (e.g., one of the uploading peers) that communicates with the different sources exchanging information about the network status and the scheduling choices of the other nodes. Unfortunately, these procedures are significantly time-demanding and need a continuous update of the network states along the different transmission paths (see [10]).

A faster solution can be obtained via a distributed classification performed independently by the single uploading peers. In this case, each source node is neither aware of the classification choices of the other source nodes nor aware of where the congestions are located. As a matter of fact, independent classification leads to contentions between different MD streams since each peer is unaware of the choices and the channel state of the other ones. It is possible to analyze the classification problem via the theoretical framework of game theory, which permits taking into account the behavior of the other nodes and granting satisfying degrees of intra-stream and inter-stream diversities in the loss patterns.

3. BASIC GAME THEORY NOTIONS AND NOTATION

A competitive behavior among a set of individuals can be represented by a "strategic game", i.e., a *model of interacting decision-makers* [11] that evaluates how each individual is affected by the actions of the others. In analytical terms, the game is identified by a set of n decision-makers (commonly-named "players"), a set $\mathscr{N}_c$ of strategies available for each individual, and a set of preferences for each player. The preferences (or utility) of the d-th player can be parameterized by a pay-off (or cost) function $f_d(\cdot)$, $d = 1,\ldots,n$, which depends on the decisions of all the players, i.e.,

$$\begin{aligned} f_d &: \mathscr{N}_c^n \to \mathbb{R} \\ f_d &: \mathbf{c} = \left[c^1,\ldots,c^n\right] \mapsto p \end{aligned} \tag{1}$$

where c^h is the strategy chosen by the h-th player, $h = 1,\ldots,n$. Assuming that players are rational and selfish, their main aim is maximizing (or minimizing) their pay-off (or cost) functions. However, a blind choice that does not take into consideration the behaviors of the other players may lead to inefficiencies whenever the game presents conflicting configurations. Assuming that players can not cooperate (*noncooperative game*), a conflict appears whenever a player needs to decrease the utilities of the other players in order to increase his/her own. As a matter of fact, the rationality of the decision-makers lead towards some points of equilibrium, where every player has no reasons to change his/her strategy as his/her utility can not improve. These configurations are called *Nash equilibria* [11], and in analytical terms, an array of strategies $\mathbf{c}^*$ is a Nash equilibrium if

$$\begin{gathered} f_d\left(\left[\mathbf{c}^{-d,*}, c^{d,*}\right]\right) \leq f_d\left(\left[\mathbf{c}^{-d,*}, c^{d}\right]\right) \\ \forall d = 1,\ldots,n \qquad \text{and} \qquad \forall c^d \in \mathscr{N}_c, \end{gathered} \tag{2}$$

where $\mathbf{c}^{-d}$ is the array of strategies of all the players made exception for the d-th, and $f_d(\cdot)$ is a cost function. In this case, no other choice allows player d to reduce $f_d(\cdot)$, therefore, the strategy $c^{d,*}$ is the best he/she can adopt. Note that this optimality must be verified for all the players at the same time making $\mathbf{c}^*$ a stable configuration.

In case players $d1$ and $d2$ can cooperate and jointly plan their strategies, it is possible to modify the original game by merging the two players into a single player D that chooses his/her strategies among a subset of $\mathscr{N}_c \times \mathscr{N}_c$ and rules his/her choices according to a common cost function $f_D(\cdot)$. In case of a nontransferable utility (NTU) games, the cost function is the same for all the players in the coalition, while in transferable utility (TU) games, there can be side payments. In our approach, we consider the first case only.

In the following, we will show how it is possible to model the distributed MDC packet classification with both noncooperative and cooperative strategic games.

4. GAME THEORY APPLIED TO MDC PACKET CLASSIFICATION

Given an MDC video sequence coded into n-descriptions, which are stored into n separate servers or uploading peers, each source node behaves like a player in an n-players game, where the d-th player (description d) can choose his/her strategy (QoS class) c_i^d for the i-th packet among a set $\mathscr{N}_c$ of N_c possible choices. The set of strategies adopted by the n players can be represented by the array $\mathbf{c}_i = \left[c_i^1,\ldots,c_i^n\right]$, and the individual cost function $f_d(\cdot)$ for each player d, $d = 1,\ldots,n$, can be characterized via some basic functions related to the network state and the features of the coded sequence.

In case players $d1$ and $d2$ cooperate to find a more effective classification strategy (coalition D), the cost function for the coalition D is $f_D(\mathbf{c}_i)$. Note that the possible strategies for $d1$ and $d2$ (represented by the couples (c_i^{d1}, c_i^{d2}) are now to be chosen within the set $\mathcal{N}_D \subset \mathcal{N}_c \times \mathcal{N}_c$. In the following sections, these functions will be described in detail.

4.1 Basic modelling functions

4.1.1 *Characterizing packet loss probability for each class*

As described before, the GT-based optimization requires some basic functions to characterize the loss probability associated to the different QoS classes. In this approach, we adopted the modellization presented in [10].

Each QoS class k can be characterized by a G/M/1/B_k^M queue model with maximum length B_k^M (expressed in terms of maximum number of packets) and with an emptying server modelled by a Poisson process with parameter λ_k. Each class is also associated to a transmission channel with loss probability P_k^{chan}, which depends on the parameter setting (e.g., the adopted channel code, the transmission power, etc.) for the k-th QoS class, and the state of the network.

When considering the best classification for the packets of description d, the loss percentages P_k^{loss}, $k = 0, 1, \ldots, N_c - 1$, are affected by the channel parameters related to the k-th class, by the parameter λ_k, and by the number of packets B_k buffered in the k-th queue. More precisely, the probability of losing the i-th packet with $B_k < B_k^M$ is

$$P_k^{loss}(\mathbf{c}_i) = P_k^{chan} + \left(1 - P_k^{chan}\right) \frac{\gamma(B_k, T_L/\lambda_k)}{\Gamma(B_k)} \tag{3}$$

where $\mathbf{c}_i$ is the classification array operated on the i-th packets of all the descriptions, $\gamma(\cdot,\cdot)$ and $\Gamma(\cdot)$ are respectively the lower incomplete and the standard Gamma functions, and the threshold T_L denotes the maximum time limit after which the packet is discarded (in our case we have set T_L to 0.2 s). For a more detailed description of the derivation process of eq. (3), we refer the reader to the paper [10].

In order to evaluate the optimality of a given configuration, it is necessary to model the distortion produced in the reconstructed video sequence by the loss of one or more descriptions. In the following subsections we will consider two different modelings for the adopted MDC schemes.

4.1.2 *Modelling distortion for the MDC scheme*

In addition to a loss probability function that models the behaviour of the channel, the optimization strategy requires an additional distortion measure that permits characterizing the expected quality of the reconstructed sequence.

A possible distortion model for an MDC scheme based on spatial polyphase subsampling can be found in [3]. In this case, it is possible to parameterize the relative quality decrement δPSNR_i^d associated to the loss of the i-th packet in description d as a linear relation

$$\delta\text{PSNR}_i^d = \frac{\text{PSNR} - \text{PSNR}_{l,i}^d}{\text{PSNR}} = h_{l,0}^d + h_{l,1}^d \rho_i^d. \tag{4}$$

The parameter PSNR in eq. (4) identifies the Peak Signal-to-Noise Ratio value of the reconstructed frame in case all the packets are correctly received, $\text{PSNR}_{l,i}^d$ is the PSNR value of the reconstructed frame when the i-th packet is lost, ρ_i^d is the percentage of null transform coefficients for the i-th packet of description d, and $h_{l,j}^d$ $(j = 0, 1)$ are the coefficients of the adopted linear distortion model. These are estimated offline from a training set of sequences.

In case descriptions $d1$ and $d2$ form a coalition D, it is possible to adopt a similar distortion model as in the case of losing a single description. The relative quality decrement related to the loss of both descriptions is

$$\delta PSNR_i^D = \frac{\text{PSNR} - \text{PSNR}_{l,i}^D}{\text{PSNR}} = k_0^D + k_1^D \rho_i^D \tag{5}$$

where $\text{PSNR}_{l,i}^D$ is the PSNR value of the reconstructed frame after losing descriptions $d1$ and $d2$ in D, ρ_i^D is the average of ρ_i^{d1} and ρ_i^{d2}, and k_0^D, k_1^D are the coefficients of the linear model that parameterizes the distortion.

4.1.3 *Building the cost functions*

Given the distortion and loss probability function, it is possible to build the cost functions f_d and f_D in order to relate the channel distortion to $\mathbf{c}_i$ and model the classification problem as a game.

From the distortion model in eq. (4), it is possible to define the individual cost function for the d-th description as the expected relative PSNR loss

$$\begin{aligned} &f_d : \mathcal{N}_c^n \to \mathbb{R} \\ &f_d(\mathbf{c}_i) = (i-1)\text{E}[f_d]_{i-1} + P_{c_i^d}^{loss}(\mathbf{c}_i)\ \delta\text{PSNR}_i^d \end{aligned} \tag{6}$$

where $\text{E}[f_d]_{i-1}$ is the average relative PSNR loss for the previous packets of the d-th description until the $(i-1)$-th instant, i.e.,

$$\text{E}[f_d]_{i-1} = \frac{1}{i-1} \sum_{t<i} f_d(\mathbf{c}_t) \tag{7}$$

for $i > 1$. A similar relation can be found for the coalition D (assuming that the coalition behaves as a single player), where the chosen function is

$$\begin{aligned} f_D(\mathbf{c}_i) = {} & (i-1)\text{E}[f_D]_{i-1} + \delta\text{PSNR}_i^D\ P_{c_i^{d1}}^{loss}(\mathbf{c}_i) \cdot P_{c_i^{d2}}^{loss}(\mathbf{c}_i) \\ & + \delta\text{PSNR}_i^{d1}\ P_{c_i^{d1}}^{loss}(\mathbf{c}_i) \cdot \left(1 - P_{c_i^{d2}}^{loss}(\mathbf{c}_i)\right) \\ & + \delta\text{PSNR}_i^{d2}\ P_{c_i^{d2}}^{loss}(\mathbf{c}_i) \cdot \left(1 - P_{c_i^{d1}}^{loss}(\mathbf{c}_i)\right) \\ \simeq {} & (i-1)\text{E}[f_D]_{i-1} + \delta\text{PSNR}_i^D\ P_{c_i^{d1}}^{loss}(\mathbf{c}_i) \cdot P_{c_i^{d2}}^{loss}(\mathbf{c}_i). \end{aligned} \tag{8}$$

In this case, the simplification is driven by the fact that the component related to a joint loss proves to be more significant than the others.

4.2 Classifying MD packets via cooperative games

The previous subsection has presented the basic functions required by the optimization process. In this subsection, we show how it is possible to classify effectively the different packets modelling the whole transmission as a cooperative game.

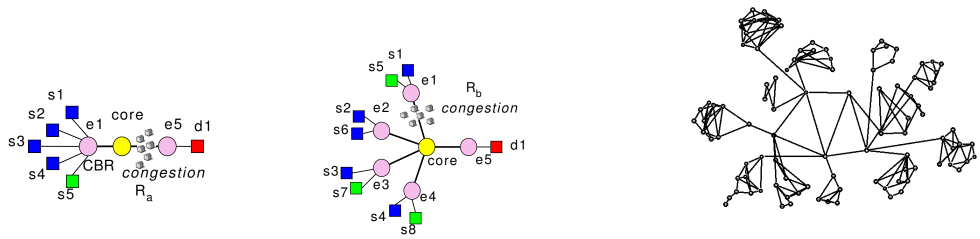
Given the classification $\mathbf{c}_i$, the loss probabilities $P_{c_i^d}^{loss}$, and the percentages ρ_i^d for the i-th packet of each description, the adopted classification strategy $\mathbf{c}_i^*$ identifies a Nash equilibrium for the game expressed by eq. (6) whenever the condition in eq. (2) is satisfied.

Assuming that coalition D is made of descriptions $d1$, $d2$ and substituting eq. (6) and (8) into equation (2), an equilibrium is found if

$$\begin{aligned} &P_{c_i^{d*}}^{loss}(\mathbf{c}_i^*) < P_k^{loss}\left(\left[c_i^{-d,*}, k\right]\right) \\ &\forall d \in \{1, \ldots, n\} \setminus \{d1, d2\} \qquad \text{and} \qquad \forall k \in \mathcal{N}_c \end{aligned} \tag{9}$$

and

$$\begin{aligned} P_{c_i^{d1*}}^{loss}(\mathbf{c}_i^*) \cdot P_{c_i^{d2*}}^{loss}(\mathbf{c}_i^*) < {} & P_{k_1}^{loss}\left(\left[\mathbf{c}_i^{-D,*}, k_1, k_2\right]\right) \\ & \cdot P_{k_2}^{loss}\left(\left[\mathbf{c}_i^{-D,*}, k_1, k_2\right]\right) \quad \forall (k_1, k_2) \in \mathcal{N}_D \end{aligned} \tag{10}$$



(a) (b) (c)

Figure 2: Network settings. a) Setting 1: congestion on a shared link (set1); b) Setting 2: congestion on a non-shared link (set2); c) Random network using GT-ITM (set3).

where $c_i^{-D,*}$ is the array c_i^* excluding the configurations for descriptions $d1$ and $d2$ of coalition D. Equation (10) identifies a set of possible Nash equilibria, and therefore, the classification strategy has to choose one of them. A possible criterion is to select the configuration that minimizes the average distortion

$$\delta\text{PSNR} = \frac{1}{n}\left\{\sum_{d\in\mathcal{N}_c\setminus\{d1,d2\}} \mathrm{E}[f_d]_i + \mathrm{E}[f_D]_i\right\}. \quad (11)$$

In this way, the algorithm avoids that one description jeopardizes all the available bandwidth in case of congestion on a shared link, and at the same time, it creates a certain differentiation between the packets belonging to the same description improving the performance in case of congestions affecting a single description.

In our simulations, MDC packets are transmitted over a DiffServ-enabled network [7], and three different priority classes $\mathcal{N}_c = \{\text{green}, \text{yellow}, \text{red}\}$ are available (see [7, 8]). For the sake of conciseness, we will refer to them with the indexes $0, 1, 2$ respectively.

In order to compute the Nash equilibria for a game with a coalition of two nodes it is necessary to define a new set of possible strategies for the coalition. In our approach, we considered two different sets $\mathcal{N}_{D1}$ and $\mathcal{N}_{D2}$ of strategies (represented by couples of labels $(c_i^{\text{MD}d}, c_i^{\text{MD}d'})$)

$$\begin{array}{l}\mathcal{N}_{D1} = \{(0,0),(1,1),(2,2)\}\\ \mathcal{N}_{D2} = \{(0,0),(1,1),(2,2),(0,1),(1,2)\}\,.\end{array} \quad (12)$$

Note that in the first set we assume that the two peers are synchronized and choose the same strategy for all the packets, while in the second set some of the strategies give a higher priority to the packet of the first peer.

Simulations results will show how the proposed classification approach proves to be extremely effective with different congestion settings.

5. SIMULATION RESULTS

Experimental tests were performed implementing a DiffServ-enabled network [7] using the NS2 simulator [12]. In the evaluation of the algorithms, we simulated the downloading of different CIF format sequences coded with fixed QP and GOP structure IPPP of 15 frames. Descriptions are ordered according to a raster scan of the pixel grids in Fig. 1. The values of the parameters λ_k, $k = 0, \ldots, N_c - 1$, were estimated from a training set of packet transmissions, while P_k^{chan} are independently evaluated by each node via the RTCP protocol. These tests aim at comparing the proposed approach with that of the GT algorithm in [3], which provides a better performance than the state-of-the-art srTCM approach in [8].

In a first set of simulations (labelled set1), we adopted the network topology shown in Fig. 2(a). The node $d1$ is downloading the MDC coded video sequence from the source nodes $s1$, $s2$, $s3$, and $s4$, while the node $s5$ is streaming a Constant Bit Rate (CBR) traffic towards the node $e5$ (with the only purpose of adding extra packets in the network). Note that description d is uploaded by the node sd. The access to the core network is ruled by the DiffServ-enabled node $e1$, and the congestion is varied reducing the available bandwidth R_a (the contention takes place on the same link).

Table 1: Labeling for coalitions between nodes.

Label	GT-COA1	GT-COA2	GT-COA3
Orient.	Horiz.	Vert.	Diag.
Nodes	$s1$,$s2$	$s1$,$s3$	$s1$,$s4$
Label	GT-COA4	GT-COA5	GT-COA6
Orient.	Horiz.	Vert.	Diag.
Nodes	$s3$,$s4$	$s2$,$s4$	$s2$,$s3$

In a second set of simulations (labelled set2), the network topology has been slightly modified, as Fig. 2(b) shows. In this case, the different MD source nodes are linked to separate DiffServ-enabled nodes (labelled as $e1$, $e2$, $e3$, and $e4$). The congestion is simulated reducing the available bandwidth R_b of the link from node $e1$ to core network, while descriptions d, $d = 2, 3, 4$, are transmitted to core network with no congestions. Nodes sk, with $k = 5, \ldots, 8$, have the only purpose of adding extra CBR packets in the network.

In the end, we considered a third test-bed (labelled set3) where a random network of 100 nodes (see Fig. 2(c)) is generated with the software GT-ITM [13], and source nodes sk, $k = 1, \ldots, 5$ and destination node $d1$ are randomly attached to 6 nodes of the random network. Congestions are created increasing the CBR traffic streamed from source $s5$ to $d1$.

In our tests, we first evaluated the transmission performance for different coalitions. More precisely, in a game of 4 descriptions/players we considered coalitions of two nodes against the other ones, which are referenced as reported in Table 1. Figure 3 shows the PSNR vs. R_a curves obtained on the network set1 for sequences coastguard and foreman coded with $QP = 28$. It is possible to notice that coalitions make possible to improve the average PSNR value of the GT approach made exception for the vertical coalitions. In fact, most of the sequences present a strong vertical correlation that allows the decoder to reconstruct the sequence with good approximation using odd or even pixel rows only since the other ones can be easily estimated. Classification results show that the coalition leads the joint nodes to choose the labels with the lowest priorities in order to ease the handling of congestion by the network, and this allows a reliable delivery of the other descriptions. Vertical coalitions lead to the loss of vertical couples of descriptions that need to be estimated exploiting the horizontal correlation. As a result, the PSNR of the reconstructed sequence is lower. The graphs also show that the most effective coalitions are the diagonal ones: whenever a diagonal couple is lost and the other is available, the missing pixels can be recovered very effectively from quincunx samples which permit obtaining a better quality with respect to rows or columns of pixels. Fig. 3(a) and 3(b) show that algorithms GT-COA3 and GT-COA6 permit increasing the average PSNR value of 1.3 dB for coastguard and 2.2 dB for foreman with respect to

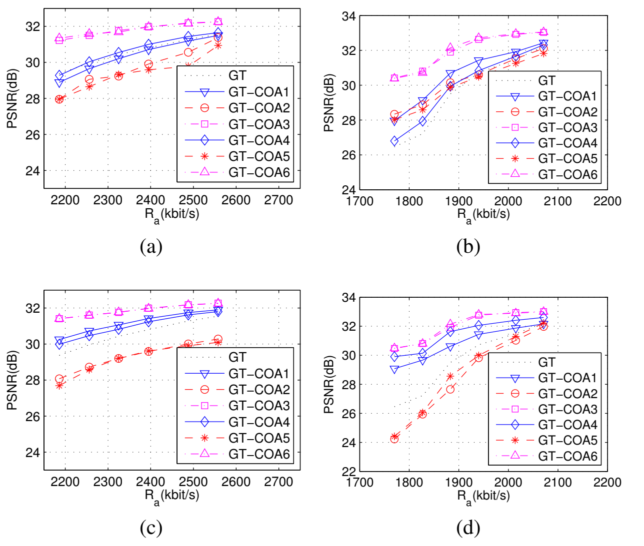


Figure 3: PSNR vs. R_a for sequences `coastguard` and `foreman` (coded with $QP = 28$) from GT optimization using noncooperative and cooperative games. Results were obtained using different sets of strategies ($\mathcal{N}_{D1}$ and $\mathcal{N}_{D2}$). a) `coastguard`, b) `foreman` with coalition strategies $\mathcal{N}_{D1}$ c) `coastguard`, d) `foreman` with coalition strategies $\mathcal{N}_{D2}$.

the GT approach.

Fig. 3(c) and 3(d) show the PSNR vs. R_a curves for the GT classification strategies using the set $\mathcal{N}_{D2}$ in place of $\mathcal{N}_{D1}$. It is possible to notice that strategies GT-COA3 and GT-COA6 still prove to be the best among all the other coalitions and the overall performances of the GT-based classifications are significantly improved for strong congestions with respect to using $\mathcal{N}_{D1}$ made exception for vertical coalitions. The PSNR difference can be at max 0.1 dB higher for diagonal coalitions, 3.11 dB higher for horizontal ones, but it can be down to 3.6 dB worse for vertical couples. The reason for this inefficiency has to be related to the poorer performance of horizontal correlation. Figure 4 reports the results obtained on network settings `set2` and `set3`. As for setting `set2`, it is possible to notice that the cooperative strategy improves the quality of the reconstructed sequence, but the gain in terms of PSNR is not relevant (about 0.25 dB on average). On the contrary, results obtained on the network setting `set3` shows that cooperative games with diagonal coalitions permits improving the average PSNR value up to 3 dB with respect to a noncooperative game with high interfering rates R_I. As a matter of fact, it is possible to conclude that solutions GT-COA3 and GT-COA6 prove to be the best for all the conditions.

6. CONCLUSION

The paper presents some classification approaches for a Multiple Description Coded video sequence which are based on cooperative games. Cooperation proves to be a winning solution since the PSNR performance improves significantly with respect to previous works based on non-cooperative games and state-of-the-art solutions. Future work will be focused on testing these algorithms with different network set-ups and different MDC solutions.

REFERENCES

[1] E. Akyol, A. Murat Tekalp, and M. Reha Civanlar, “A flexible multiple description coding framework for adaptive peer-to-peer video streaming,” *IEEE J. Select. Topics Signal Processing*, vol. 1, no. 2, pp. 231 – 245, Aug. 2007.

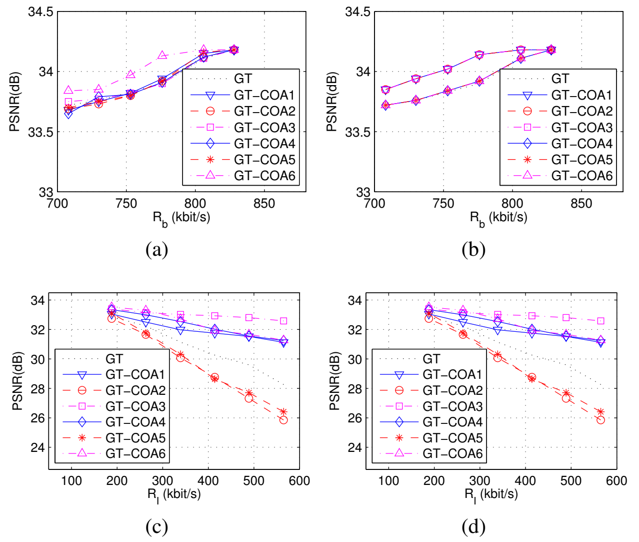


Figure 4: PSNR vs. R_b and R_{CBR} for the sequence `foreman` (coded with $QP = 28$) over different networks ($\mathcal{N}_{D1}$ and $\mathcal{N}_{D2}$). a) `set2` with $\mathcal{N}_{D1}$, b) `set2` with $\mathcal{N}_{D2}$, c) `set3` with $\mathcal{N}_{D1}$, d) `set3` with $\mathcal{N}_{D2}$.

[2] V. K. Goyal, “Multiple Description Coding: Compression Meets The Network,” *IEEE Signal Process. Mag.*, vol. 8, no. 5, pp. 74–93, Sept. 2001.

[3] S. Milani and G. Calvagno, “A Game Theory Based Classification for Distributed Downloading of Multiple Description Coded Videos,” in *Proc. of the IEEE ICIP 2009*, Cairo, Egypt, Nov. 24 – 28, 2009, pp. 3077 – 3080.

[4] X. Wu, B. Ma, and N. Sarshar, “Rainbow network problems and multiple description coding,” *IEEE Trans. Inf. Theory*, vol. 54, no. 10, pp. 4565 – 4574, Oct. 2008.

[5] Simone Zezza, Enrico Magli, Gabriella Olmo, and Marco Grangetto, “SEACAST: a protocol for peer-to-peer video streaming supporting multiple description coding,” in *Proc. of ICME 2009*, New York, USA, June 28 – July 3, 2009.

[6] D. Schmidt, C. Shi, R. Berry, M. Honig, and W. Utschick, “Distributed resource allocation schemes,” *IEEE Signal Process. Mag.*, vol. 26, no. 5, pp. 53 –63, Sept. 2009.

[7] S. Blake, D. Black, M. Carlson, E. Davies, Z. Wang, and W. Weiss, “An Architecture for Differentiated Service,” RFC 2475, Dec. 1998.

[8] J. Heinanen and R. Guerin, “A Single Rate Three Color Marker,” RFC 2697, Sept. 1999.

[9] R. Bernardini, M. Durigon, R. Rinaldo, P. Zontone, and A. Vitali, “Real-Time Multiple Description Video Streaming Over QoS-Based Wireless Networks,” in *Proc. of International Conference on Image Processing (ICIP 2007)*, San Antonio, TX, USA, Sept. 2007, pp. 245 – 248.

[10] Simone Milani and Giancarlo Calvagno, “Improving Quality-of-Experience for Multiple Description Video Transmission in Peer-To-Peer Networks,” in *Proc. of ACM Workshop on Advanced Video Streaming Techniques for Peer-to-Peer Networks and Social Networking (ACM MM 2010)*, Florence, Italy, Oct.29, 2009, pp. 65 – 69.

[11] M. J. Osborne, *An Introduction to Game Theory*, Oxford University Press, 2004.

[12] “The Network Simulator NS-2,” http://www.isi.edu/nsnam/ns.

[13] “Modeling Topology of Large Internetworks: GT-ITM software,” http://www.cc.gatech.edu/projects/gtitm/.