Improving Quality-of-Experience for Multiple Description Video Transmission in Peer-To-Peer Networks

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ABSTRACT

Recent works have shown how the transmission of multimedia data over Peer-to-Peer networks is significantly improved by the adoption of Multiple Description Coding (MDC) techniques. However, the performance of these schemes can be significantly enhanced by differentiating the Quality-of-Service levels for the transmitted data in order to grant intra-stream and inter-stream diversities among the loss patterns affecting the different descriptions. The paper presents a classification algorithm that addresses a four description MDC scheme and adopts an optimization strategy based on modelling the transmission of packets like a noncooperative game. Different peers are considered as independent players competing for the network resources. The proposed approach improves the quality of the reconstructed sequence without the need of a coordinating node or message passing between the uploading peers.

Categories and Subject Descriptors

I.4.9 [**Image Processing and Computer Vision**]: Applications; H.3.4 [**Systems and Software**]: Distributed Systems

General Terms

Algorithms, Design, Measurements, Performance.

Keywords

Cross-layer optimization, P2P video, multiple description, packet classification, game theory.

1. INTRODUCTION

Peer-To-Peer (P2P) data delivery protocols permit an effective and flexible delivery of multimedia data via the interconnection and the cooperation of the different nodes in the network (peers). As a matter of fact, research activity has been dedicated worldwide to the development of novel video coding architectures that fit the characteristics of P2P systems. Multiple Description (MD) architectures [1] prove to be an effective solution for P2P video transmission since they permit solving several problems concerning the varying topologies of Peer-To-Peer networks. The original video source is coded into multiple chunks of correlated data (descriptions), which are coded and transmitted independently [2]. The correlation existing among different streams permits estimating the lost data by mutually approximating the lost description from the available ones. Despite MD schemes have proved to be extremely effective in most scenarios, experimental results show that the effectiveness of such approaches depends on how MD packets are routed and transmitted [3]. In relation with P2P networks, 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 the 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 involved in the data delivery. 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 [6].

This paper presents a cross-layer distributed classification algorithm based on the principles of Game Theory (GT) for the delivery of Multiple Description sequences over P2P networks. Packets are scheduled into multiple QoS classes via a noncooperative game that aims at minimizing the channel distortion affecting each stream and the final reconstructed sequence. Previous works [7] employed a simple 2 descriptions MD scheme and did not take into account the balancing between the needs of providing a certain degree of diversity within the same bit stream and among different descriptions. The proposed approach has been applied to a 4 descriptions MD sequence, and it proves to be an effective solution with respect to other independent scheduling approaches both in case the network congestion affects all the descriptions (i.e. peers are competing among each others) and in case it affects just one MD stream. In fact, the

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proposed strategy finds an effective trade-off between *intra stream diversity* and *inter stream diversity*.

The rest of the paper is organized as follows. Section 2 presents the adopted Multiple Description strategy, while Section 3 describes how the packets are classified into multiple classes. Section 4 tests the proposed strategy under different network conditions. Conclusions are drawn in Section 5.

2. MULTIPLE DESCRIPTION CODING OF VIDEO SEQUENCES

Since the earliest Multiple Description coding scheme for video transmission proposed in literature [2], several different MD architectures have been designed. The effectiveness of these solutions varies significantly according to the target application and the transmission scenario. In our approach, we adopted one of the first MD strategies, which is based on a simple 2-D polyphase subsampling of the pixels in each frame. The rationale of our choice relies on the fact that this approach is quite general and has been widely studied. Moreover, the results obtained with this architecture can be easily extended to other approaches.

Given the input frame $F(n, m)$, the MD generation unit partitions the input samples into four subsequences $F(2\,i, 2\,j)$, $F(2\,i+1, 2\,j)$, $F(2\,i+1, 2\,j)$, and $F(2\,i+1, 2\,j+1)$, with $i = 0, \ldots, \lfloor h/2 \rfloor$ and $j = 0, \ldots, \lfloor w/2 \rfloor$ where h and w are the number of pixel rows and columns of the input video sequence. As a result, the input video sequence is split into four subsequences with halved spatial resolution and different phases. Each subsequence is then independently coded by an H.264/AVC codec and uploaded in the network in separate repositories. The intrinsic correlation existing among adjacent pixels permits estimating each subframe from the other ones via a linear interpolation. In our implementation, we adopted a simple interpolation approach based on averaging the neighboring pixels, but more complex adaptive strategies can be designed. Note that the quality of the reconstructed subsequence increases as the number of available correlated pixels augments. In case all the descriptions have been lost, the missing data have to be estimated like in the Single Description (SD) coding case (i.e. by copying the missing parts from the previously correctly-decoded frame).

The performance of the designed MD scheme can be improved by effective algorithms that classify packets varying their loss probabilities [3]. The following section presents a possible strategy.

3. DISTRIBUTED CLASSIFICATION FOR MD VIDEO PACKETS

The performance of MD coding can be significantly improved via an effective packet classification whenever the transmitting network permits specifying different QoS classes for each packet. Each class $c \in \mathcal{C}$, where $\mathcal{C}$ is the set of all possible classes, can be characterized with different number of retransmissions, contention handling, priority ranking and handling strategy in case of congestions. As a result, the loss probability can vary significantly according to c. In this way, it is possible to increase the diversity between the loss patterns experienced by the different MD streams minimizing the probability that no descriptions are available [3]. Several classification strategies have been proposed in relation with wireless networks, where the MD strategy permits obtaining a better error resilience with respect to the single description strategies despite the high loss rates. However, whenever dealing with a distributed transmission scenario like those of P2P and Content Delivery Network (CDN), the classification task becomes more complex since descriptions are stored in separate peers or servers whose transmission channels can be quite different and unknown to the other peers. As a matter of fact, the nodes must be endowed with a distributed classification algorithm that varies the priority of the video packets being aware that other nodes are trying to transmit packets to the same destination and could be competing for the usage of network resources.

3.1 Quality metrics for packet classification

Previous works [7] have shown that each transmitting peer has to grant a certain degree of diversity both among the loss patterns regarding packets of the same stream with different significances (*intra stream diversity*) and regarding different descriptions (*inter stream diversity*).

Intra stream diversity must be obtained by minimizing the probability of losing the RTP packets of the same description which result crucial in the decoding process. As a matter of fact, it is necessary to characterize the significance of the packets by estimating the channel distortion produced in the reconstructed sequence by their loss. In our implementation, we adopted the ρ-based approach of [3], which parameterizes the relative PSNR decrement $\delta\mathrm{PSNR}_{i,j}$ related the the loss of the j-th packet of the i-th description as

$$\delta\mathrm{PSNR}_{i,j} = \frac{\mathrm{PSNR}_o - \mathrm{PSNR}_{i,j}}{\mathrm{PSNR}_o} = k^l_{i,0} + k^l_{i,1}\rho_{i,j} \qquad (1)$$

where PSNR_o and $\mathrm{PSNR}_{i,j}$ are the PSNR values for the full-resolution frame related to the j-th packet reconstructed at the decoder with no packet loss and after losing the j-th packet of description i, respectively ($i = 1, \ldots, N_d$ where N_d is the number of descriptions). The parameter $\rho_{i,j}$ is the percentage of null quantized transform coefficients for the j-th packet of description i, and $k^l_{i,0}$, $k^l_{i,1}$ are the parameters of the linear distortion model, which are estimated from the experimental data (see [3]). From these premises, a sensible classification algorithm would make the loss probability of the packets decreases as $\delta\mathrm{PSNR}_{i,j}$ increases in order to minimize the final distortion, i.e. in mathematical terms

$$\mathbf{c}^*_{i,\cdot} = \arg \min_{\mathbf{c}_{i,\cdot} \in \mathcal{C}^{N_p}} \sum_{j \in W_p} \delta\mathrm{PSNR}_{i,j}\ p_{l,j}(c_{i,j}) \qquad (2)$$

where $\mathbf{c}_{i,\cdot}$ is the array of classes for the N_p packets of description i in the interval W_p (in our approach W_p is the time-domain for the minimization). The function $p_{l,j}(c)$ maps the chosen class c for the j-th packet to the relative loss probability; its value depends on the number of packets previously-assigned to the class (i.e. on $c_{i,t} = c$ with $t < j$ and $\forall i$) and on the number of packets from the other descriptions assigned to the same class (i.e. on $c_{d,j} = c$ with $d \neq i$).

As for the Inter stream diversity, the classification approach has to minimize the number of descriptions that are jointly lost in the transmission by differentiating the loss probability of the various descriptions. In this case the worst condition is met whenever no description is correctly received. Using the same notation of eq. (2) and grouping the classification choices $c_{i,j}$ for different descriptions in the array $\mathbf{c}_{\cdot,j}$, it is possible to minimize the worst case effects via the classification

$$\mathbf{c}^*_{\cdot,j} = \arg \min_{\mathbf{c}_{\cdot,j} \in \mathcal{C}^{N_d}} \prod_{i=1}^{N_d} \delta\text{PSNR}_{i,j}\ p_{l,j}(c_{i,j}). \tag{3}$$

It is possible to take into consideration both requirements by minimizing the function

$$\begin{aligned} D_i\left(\mathbf{c}_{\cdot,\cdot}\right) = \sum_{j \in W_p} \{&\alpha\ \delta\text{PSNR}_{i,j}\ p_{l,j}(c_{i,j}) + \\ &(1-\alpha) \prod_{i=1}^{N_d} \delta\text{PSNR}_{i,j}\ p_{l,j}(c_{i,j}) \Big\} \end{aligned} \tag{4}$$

which combines both equations (2) and (3) via the proportional weight α, with $0 \leq \alpha \leq 1$. The array $\mathbf{c}_{\cdot,\cdot} \in \mathcal{C}^{N_p\ N_d}$ of classes $c_{i,j}$ denotes the class configuration for the current GOP. The parameter α balances the influence of inter and intra stream diversities, and it should be related with the characteristics of the coded sequence.

For sequences with high spatial correlation and low temporal correlation, lost descriptions can be easily estimated from the available ones, and therefore, providing a high degree of diversities among the different MD streams (inter stream diversity) increases the robustness of the transmission. On the other hand, the visual quality of the reconstructed sequences with low spatial and high temporal correlations is poorly affected by inter stream diversity and proves to increase whenever inter stream diversity is preserved. As a matter of fact, the parameter α has to be tuned according to the spatial correlation of the coded sequence. In our implementation, we set α as

$$\alpha = 1 - \frac{R_S - 4}{16} \qquad \text{with } R_S = \frac{|S_x| + |S_y|}{|\Delta_t|} \tag{5}$$

where S_x, S_y are the average vertical and horizontal Sobel operators and Δ_t is the average temporal gradient. The value of α is clipped within the range $[0, 1]$. The ratio R_S compares the spatial and temporal correlation (measured via the Sobel operators and the temporal gradients, respectively). As a matter of fact, equation (5) linearly relates the weight of intra and intra stream diversities with the effectiveness of error concealment in MD coding.

Equation (4), together with the parameter adaptation of eq. (5), provides an effective metric that can be used to minimize the channel distortion on the final reconstructed sequence at the decoder. Despite the minimization problem proves to be simple in a centralized approach where a single terminal classifies all the packets, the classification task proves to be more complex in a distributed scenario where each stream/description is classified independently by separate nodes that can not communicate and are completely unaware of the choices of the other nodes. This assumption is supported by the fact that a message exchange among the different peers in order to communicate their states and coordinate the classification choice would imply an additional delay in the transmission and, as a consequence, a reduced effectiveness of the approach (channels statistics could result obsolete). It is possible to accomplish a more effective classification via a distributed independent GT-based optimization.

3.2 A distributed classification strategy based on a noncooperative game

Previous works have already shown how it is possible to model the problem of distributed packet classification using the principles of Game Theory. The nodes uploading the different descriptions in the network can be seen as players competing for the network resources (i.e. the possibility of transmitting successfully the different packets). 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. More precisely, players aim at transmitting packets with highest priorities, but all of them are aware that in case too many packets are injected in the network with the same classification, packet traffic would congest and the benefits of supporting different QoS classes would be null. Since each peer ignores the choices of the other terminals, it is possible to model the classification with a noncooperative game. Assuming that each uploading peer is transmitting one description, in the following we will use the same index i to denote both the description and the peer (also referred as "player").

Whenever peers are transmitting the j-th packet, the preferences (or utility) of one player can be parameterized by a pay-off (or cost) function

$$\begin{aligned} &f_{i,j} : \mathcal{C}^{N_d} \rightarrow \mathcal{R} \\ &f_{i,j} : \mathbf{c}_{\cdot,j} = [c_{1,j}, \ldots, c_{N_d,j}] \mapsto p \end{aligned} \tag{6}$$

with $i = 1, \ldots, N_d$. In our implementation, the cost function $f_{i,j}$ is the estimated distortion $D_i(\cdot)$ with $W_p = [0, \ldots, j]$ where all the classification choices prior to instant j (i.e. $c_{\cdot,k}$ with $k < j$) have already been determined in the previous instants. As a matter of fact, it is possible to define $f_{i,j}(\mathbf{c}_{\cdot,j})$ recursively as

$$f_{i,j}(\mathbf{c}_{\cdot,j}) = \sum_{t=0}^{j-1} f_{i,t}(\mathbf{c}_{\cdot,t}) + D_i(\mathbf{c}_{\cdot,j}) \tag{7}$$

with $W_p = \{j\}$.

The rationality of the decision-makers and the correctness of their beliefs about the actions of the other players 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* [8], and in analytical terms, an array of strategies $\mathbf{c}^*_{\cdot,j}$ is a Nash equilibrium if

$$f_{d,j}\left(\left[\mathbf{c}^*_{\sim d,j}, c^*_{d,j}\right]\right) \leq f_{i,j}\left(\left[\mathbf{c}^*_{\sim d,j}, c_{d,j}\right]\right) \tag{8}$$

$\forall d = 1, \ldots, n$, $\forall c_{d,j} \in \mathcal{N}_c$. The array $\mathbf{c}^*_{\sim d,j}$ contains the strategies $c^*_{i,j}$ in $c^*_{\cdot,j}$ of all the players $i \neq d$ and $f_{d,j}(\cdot)$ is the cost function.

In our implementation, at each time instant j the algorithm evaluates the cost functions $f_{d,j}$ for all the possible configurations $\mathbf{c}_{\cdot,j}$ and identifies those configuration that are Nash equilibria. Given the set $\mathcal{N}_e$ of Nash equilibria, the optimization routine looks for the configuration that minimize the overall distortion, i.e.

$$\mathbf{c}^f_{\cdot,j} = \arg \min_{\mathbf{c}_{\cdot,j} \in \mathcal{N}_e} \sum_{d=1}^{N_d} f_{d,j}(\mathbf{c}_{\cdot,j}). \tag{9}$$

3.3 Modelling QoS classes in the optimization approach

A key element in the optimization performed by the non-cooperative game described in the previous subsection is the parameterization of the packet loss statistics for the different QoS class.

Each class k can be modelled via a queue 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. The parameter λ_k varies according to the congestion level of the network and the transmission priority associated to the k-th class, which changes the probability of accessing the medium and, as a consequence, the waiting time. Each class is also associated to a transmission channel with loss probability $P_{chan,k}$, 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 network. Since packets are transmitted by each source at a constant packet rate, it is possible to model each QoS class with a G/M/1/B_k^M queue model, where the generic arrival rate depends on the classification choices of the algorithm.

Assuming that B_k is the number of packets buffered in the k-th queue (with $B_k < B_k^M$), the loss probability $p_{l,k}$ for the i-th description can be written as

$$p_{l,k}(c_{i,j}) = P_{j,k}^{late}(B_k) + \left(1 - P_{j,k}^{late}(B_k)\right) P_{chan,k} \qquad (10)$$

where $P_{j,k}^{late}(B_k)$ is the probability for the class k that the i-th packet can not be delivered in time (i.e. later than a certain time limit), and $P_{chan,k}$ characterizes the packet loss probability related to the network congestion level. Whenever $B_k = B_k^M$), the loss probability $p_{l,k}(c_{i,j})$ is equal to 1. Note that $P_{chan,k}$ can vary for the different uploading nodes since network states can differ throughout the network. Unfortunately, the lack of messaging between source terminals makes each node unaware of the transmission conditions for the other terminals, and therefore, it is not possible to obtain a global optimum for the labelling process. As a matter of fact, $P_{chan,k}$ corresponds to the loss probability measured by the node itself via some transmission control protocol and may differ from the actual values throughout the network. In our case, the transmission control information is provided by RTCP packets which are defined within the RTP specifications and contain additional information about packet losses and throughput.

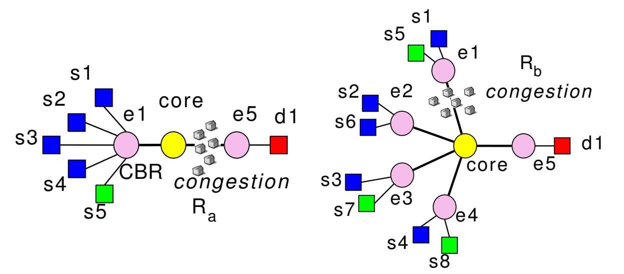
The probability $P_{j,k}^{late}(B_k)$ can be expressed as

$$P_{j,k}^{late}(B_k) = P\left[\sum_{m=0}^{B_k-1} \Delta T_m > T_L\right] \qquad (11)$$

where ΔT_m is the waiting time for the m-th buffered packet after the $(m-1)$-th packet has been served, and the threshold T_L denotes the maximum time limit after which the packet is discarded since it has become obsolete (in our case we have set T_L to 0.2 s). Assuming that the waiting time ΔT_m is an exponential variable, the overall waiting time for the m-th buffered packet is an Erlang variable, and the resulting probability of losing the m-th packet ($B_k < B_k^M$) is

$$p_{l,k}(\mathbf{c}_{\cdot,j}) = P_{chan,k} + (1 - P_{chan,k})\ \frac{\gamma(B_k, T_L/\lambda_k)}{\Gamma(B_k)} \qquad (12)$$

where $\gamma(\cdot,\cdot)$ and $\Gamma(\cdot)$ are the lower incomplete and the standard Gamma functions, respectively.



(a) (b)

Figure 1: Network settings: a) congestion on a shared link; b) congestion on a non-shared link.

Experimental results in the following section prove that the modellization choices are accurate enough to improve the quality of the reconstructed sequence at the end terminal.

4. EXPERIMENTAL RESULTS

The performance of the proposed classification algorithm has been measured over different kinds of networks and topologies. In this paper we will consider the special case of DiffServ networks [9], where packets are classified into three classes ($N_c = 3$), but it can be extended to other QoS-aware networks. The values of the parameters λ_k, $k = 0, \ldots, N_c - 1$, were estimated from a training set of packet transmissions, while $P_{chan,k}$ are independently evaluated by each node via the RTCP protocol.

The algorithm was tested on two different types of congestion, where inter-stream and intra-stream diversities are respectively required in the loss patterns. More precisely, we adopted two different network settings designed in such a way that congestions affect data streams from different peers (see Fig. 1(a) and 1(b)). In both scenarios, the node d1 is downloading the MDC coded video sequence from the source nodes s1, s2, s3, and s4 while the nodes s5, s6, s7, and s8 are streaming Constant Bit Rate (CBR) traffic towards the node e5. The node si, with $i = 1, \ldots, 4$, stores the i-th description of the MDC video sequence, which has been coded using the H.264/AVC coder with fixed QP, GOP structure IPPP, and CABAC entropy coding. The original video sequence has been captured with CIF resolution at 30 frame/s. Node sk, with $k = 5, \ldots, 8$, has the only purpose of adding extra CBR packets in the network. The DiffServ-enabled nodes e1, e2, e3, e4, and e5 [9] process the packets according to their labels and to the buffer levels. In one case, the congestion is varied reducing the available bandwidth R_a of the link from the the core network to node $e2$ (configuration a). In the second case, the congestion is varied reducing the available bandwidth R_b of the link from node $e1$ to core network (configuration b). In this way, congestion affects all the uploading peers in the first case and only node $s1$ in the second one. The performance of the GT-based approach (labelled GT2 in the reported graphs) is compared with the performances of the classification strategy in [7] adapted to 4 MDC descriptions (labelled GT), the Algorithm 1 proposed in [3] (labelled ρ-based) and with the standard technique TRTCM [10]. The simulation results reported in Fig. 2 show that the GT2 approach improves the PSNR value up to 2.5 dB for the sequence `foreman` (see Fig. 2(a)) with respect to the TRTCM approach. Note also that the GT approach in [7] does not perform quite effec-

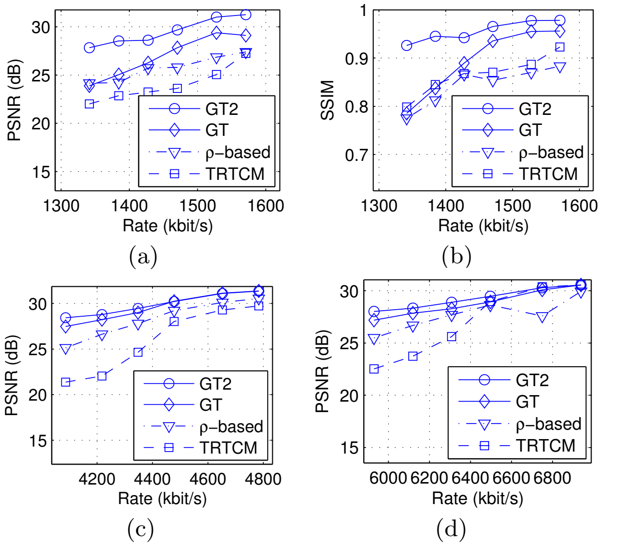


Figure 2: Average quality metrics vs. the transmission rate R_a for different algorithms in setting a) ($QP = 30$). The plots report the PSNR values for the sequences `foreman` (a) , `flower` (c), `mobile` (d), and the SSIM value for `foreman` (b).

tively on a 4-descriptions MDC streams. This improvement can be verified by considering different quality metrics as well (see Fig. 2(b) which reports the average values of SSIM metrics for the sequence `foreman` coded with $QP = 25$). A quality improvement can be noticed for other sequences as well (see Fig. 2(c) and Fig. 2(d)).

In addition, the proposed strategy proves to be effective in the second scenario as well (see Fig. 3). The reported data show that for the sequence `foreman` the GT2 approach improves the PSNR of 1.5 dB with respect to the ρ-based approach and of 0.7 dB with respect to the GT approach with $R_b = 300$ kbit/s (see Fig. 3(a)). An improvement can be noticed for the sequence `flower` as well (Fig. 3(b)), where an improvement of 1.5 dB can be noticed at high congestion levels. Additional results show that the improvement brought by the GT2 approach with respect to TRTCM strategy varies less significantly according to the characteristics of the coded sequence, while the improvement of the GT approach proves to be strictly depending on the coded video sequence. This fact is mainly due to the adoption of the weighting factor R_S, which takes into account of the spatial correlation in the distortion metrics and permits improving the quality of the reconstructed sequence with respect to the approach in [7], where there is no distinction between intra and inter stream diversity.

5. CONCLUSIONS

The paper presents a classification approach for an Multiple Description Coded video sequence which is based on a noncooperative game and employs a cost function that balances both intra and inter stream diversities according to the characteristics of the coded video sequence. The approach enhances the visual quality of the reconstructed sequences (measured via different quality metrics) both in case the congestion affects a network link shared by the different descriptions and in case the congestion only affects a single

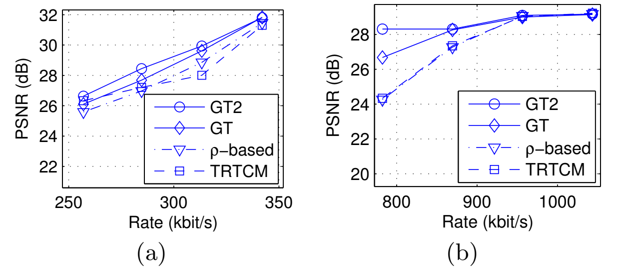


Figure 3: Average PSNR vs. the transmission rate R_b for different sequences coded in the setting b) ($QP = 30$). a) `foreman` b) `flower`.

description. In the future, research work will be focused on improving the performance of this approach by permitting the different peers to share some statistics about the network state. Moreover, the investigation will consider modelling the optimization problem via different kinds of games that allow the cooperation between the nodes.

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