Cooperative Application Layer Joint Video Coding in the Internet of Remote Things

Igor Bisio, Fabio Lavagetto, Giulio Luzzati

Abstract—Recently the problem of interconnecting Internet of Things (IoT) nodes when they are dispersed over wide geographical areas has been highlighted: this is the Internet of Remote Things (IoRT). It could be able to play a key role in disaster recovery scenarios (e.g., earthquakes, flash floods, terrorist attacks, etc.) where the presence of a communication infrastructure enabling video transmissions from the emergency areas is crucial. Local communications can be provided by Incident Area Networks (IAN), while satellite communication systems can bridge the gap towards external networks. In this context we propose a cooperative resource allocation mechanism, which exploits feedback from links conditions and knowledge of the adaptive coding, allowing a higher quality and more fair experience for all nodes of the IoRT transmitting videos. We implemented each element of the mentioned scenario over an emulation platform to prove the concept and show the obtained benefits.

I. INTRODUCTION

The Internet of Things (IoT) has drawn great attention from the scientific community because of the numerous scenarios and opportunities it anticipates [1]. In this new paradigm a network is populated with objects that take active part in it, by communicating and interacting with other network nodes or with the environment in which they operate. The enabling elements of the envisaged IoT scenarios are the Smart Objects (SO), a term which defines a physical object enhanced with communicating capabilities, whose roles are such as sensing, actuating, relaying, etc.

A. The Internet of Remote Things

The research community has recently highlighted the problem of interconnecting sensors, actuators and SOs in general, when they are possibly dispersed over wide geographical areas [2]: this kind of network has been referred to as the Internet of Remote Things (IoRT) [3]. Prominent examples of applications in which the IoRT could be able to play a key role are those such as emergency management and disaster recovery scenarios, in case of which the presence of a communication infrastructure is paramount in order to coordinate rescue and responding operations. Earthquakes, flash floods, and possibly terrorist attacks are often followed by the disruption or outage of the existing communication infrastructure (e.g., the common cellular network). The deployment of wireless ad-hoc networks such as Incident Area Networks (IAN) [4] has been proposed, exploiting the flexibility of self-organizing temporary wireless networks. While IANs alone can provide only a local infrastructure in the disaster area, the communications with remote Emergency Control Centers (ECC) can be enabled by Long Range Networks (LRN), which are likely based on satellite communication systems.

Such infrastructures aimed for deploying communication in disaster areas have been investigated in the literature, where local on-site networks (i.e., the IANs) are meant to be bridged to the Internet via gateways [5]–[7], possibly using Unmanned Aerial Vehicles (UAV) [8].

[3] defines two ways of designing communications between the satellite and the elements of a IAN, namely direct and indirect access mode. In the first case every node is able to directly communicate with satellites, while in the indirect the IAN elements communicate through a gateway node (GW). The indirect mode allows to offload the burdensome aspects of satellite communications from the IoRT nodes in the IAN, which can thus gain in operational lifespan and cost-effectiveness.

The application considered in this article is contextualized in the aforementioned scenario, considering indirect mode communications. In this context, we consider the ECCs requiring a small (1-4) number of video feeds from the disaster area scene in order to properly assist the rescue and responding operations. While other nodes may of course be participating in the IAN within the IoT paradigm, we consider the subset of all the nodes enabled with video transmission capabilities. It is important to notice that the IAN infrastructure is intended to provide communications to a limited set of users, i.e., it is not a public access infrastructure. A plausible example is given by first responders on site which are equipped with ordinary smartphones, and are thus able to provide the required video streams (Fig. 1)

![Fig. 1. The proposed reference scenario.](image)

While it is critical that the received video could be experienced with an adequate level of Quality of Experience (QoE) [9] in order to be useful to the rescue teams, the described scenario presents multiple obstacles to this aim: one example is represented by areas within the IAN where the wireless link is intermittently shadowed or poor in SNR, e.g. towards the edge of the IAN.
B. Emergency Video Transmission

Channel and source coding are critical in this context, since the first is needed to render the communication able to survive the errors and the latter is fundamental in adapting the offered load to the available resources. Static coding, and fixed resource allocation are not optimal solutions with respect to the overall QoE and fairness among users. For this reason, in this paper, extending the concepts preliminarily proposed in [10], we propose the employment of i) a dynamic transmission rate allocation, aimed at granting the fairest share of resource to each user, jointly and in cooperation with ii) an application layer joint coder for video transmission capable of computing optimal source and channel coding parameters according to varying channel conditions. We consider a non uniform resource allocation, such that “good state” links can be able to forgo some of their share of resource for the benefit of impaired links. The rationale for this work is the highly non linear behaviour of typical rate/distortion curves of source coders (Fig. 2). The high-rate region of the curve shows asymptotical behaviour for distortion values approaching zero: a small increase in distortion can allow a significant decrease in the required rate. This means that moving resources from high-rate, “good state” links to impaired ones which are struggling in low-rate region can be globally beneficial because impaired links can gain more than what “good states” lose.

Typically, control techniques are employed independently of each other; in this paper we present a solution that considers and evaluates the effect of the joint employment of the mentioned techniques on the system performance.

From the technical viewpoint, we consider applications implementing the roles of transmitters and receivers, based on the Android OS, designed and developed by the authors. The applications are also implementing Application Layer Joint Coding (ALJC) algorithms for video compression, protection and transmission [12]. Briefly recalling the concept of ALJC, given a measure of the experienced packet loss, the transmitter decides a suitable protection level in response to channel conditions by appropriately setting the code rate, then selects the maximum allowable quality video coding parameter given the estimated network allowable throughput.

The main contribution of this paper consists in a centralized entity performs a Transmission Rate Allocation (TRA), and by letting it be aware of the ALJC algorithm and of the link conditions (i.e., each signal to noise ratio $SNR$ for example), it can perform a non uniform allocation of the total network resource. This consists in the allocation of shares of the overall available rate to each source-destination couple, with the goal to maximize the average QoE and its fairness experienced by users.

The rest of the paper is organized as follows: in Section II the reference scenario and a brief survey of the related literature is presented. In Section III and IV the employed ALJC and the Transmission Rate Allocation (TRA) are described, respectively. The performance investigation and the obtained results are discussed in Section V. Finally conclusions are drawn.

II. SCENARIO AND STATE OF THE ART

The reference model for this paper is depicted in Figure 3. It consists of $Z$ sources communicating with remote destinations, while sharing a common link with an overall available transmission rate equal to $R_{TOT}$. Each source-destination couple constitutes a path, which is granted a portion of the overall transmission rate $R_z$.

![Fig. 3. Model of the problem.](image)

The Application Layer Joint Coding (ALJC) solution considered in this paper has been originally presented in [12] and was inspired from works in the literature such as [13], where the partition of the communication system space in two sub-spaces called performance regions is argued, and it is shown that the employment of application layer channel coding is advantageous in one region, while it proves detrimental in the other one. The first performance region contains the systems that experience good channel and low loss probability. The second is the region of the systems working with highly errored channels. The application layer channel coding is beneficial only for the first region, since communications in the second require such high redundancy that the congestion effects tend to prevail. An approach working around this effect is proposed in [14, Chapter 1]: high redundancy does not result in an increased load, because it results in lower information rates instead of increased transmission rates. Our approach follows this paradigm, whereas the transmission rate is a constraint continuously estimated, thus keeping the network load under control. On the other hand, in case of high error rates, low code rates are adopted which result in reduced net information rate and thus size of sent video frames. For this reason,
an end-to-end distortion minimization algorithm had to be devised, entailing a joint source-channel coding problem. For what concerns the multi-user resource allocation, several interesting works can be found in the literature, such as [15], [16], [17], [18] and [19]. In particular, [20] deals with the resource allocation modelled as a competitive problem where entities compete with each other to obtain part of the available resource. In more detail, the competition may take place among the users sharing the same satellite resource, or among contrasting goals such as QoE and power consumption metrics of a single user. In this context, we employ Multi Objective Programming (MOP) theory [21], allowing the joint optimization of multiple metrics and providing a set of solutions defined as a Pareto Optimal Point (POP) set. In order to choose a single point within the POP set we reformulate the problem according to the \( L_p \)-problem theory [22] as proposed in Section IV.

III. APPLICATION LAYER JOINT CODING ON SMARTPHONES

Our heuristic ALJC solution controls source and channel coding jointly and considers the communication network as a black box through which the \( z \)-th transmitter and receiver want to communicate. The applications implementing ALJC use a simple intra-frame only video coder and a packet-level forward error correction (FEC) code. Packet-level FEC are able to recover the loss of whole packets, and thus codewords consists of multiple packets. The codrate is hence the ratio of information packets over the total number of packets in the codeword.

This ALJC mechanism requires knowledge of the evolution of the network conditions, which are estimated by means of a feedback from the receiver, containing information about the amount of lost packets for each received codeword and their timing.

In this way the transmitter can infer \( i \) the network throughput and \( ii \) the experienced loss, and consequently control the transmission rate, the required redundancy and the highest allowable image compression.

Channel and source coding are controlled using two parameters: \( i \) the codrate \( (C_r) \), defined above, and \( ii \) the video coder quality parameter \( (Q) \), which is related to the transmitted frame size \( F_s \) as described in the following. The aim is to dynamically determine the best operating point, maximizing QoE as a function of the state of the network.

In our system, the receiver sends a report packet for every codeword, allowing the transmitter to update its state. Each time a report packet is received, the transmitter performs the ALJC algorithm which reported in the flow chart in Fig. 4.

A. Code Rate Selection

The first step of the ALJC algorithm consists in the assessment of the codrate required given the experienced packet loss of the receiver. The channel code is a packet-level Raptor Code [23]. It belongs to the class of fountain or rateless codes because of their ability to generate a potentially infinite sequence of repair symbols (i.e., packets). For our system, we define a codeword as a group of 35 packets. Referring to classical channel code literature notation, the code rate of a code is defined by \( C_r = \frac{k}{n} \), so we let \( n = 35 \). In each codeword, part of the packets are information packets \( (k) \), while the remaining \( n-k \) is composed by redundancy (repair) packets. Using channel coding, for a given packet loss rate, there exists a certain code rate that ensures an arbitrarily low residual error after decoding.

In order to find such relation we generated a large number of codewords varying the codrate \( C_r \). For each \( C_r \) value we punctured packets according to packet loss rate \( P_l \) (in the range \([0\%, 99\%]\)). Finally, we decoded and measured the residual error, whose expected value obtained by averaging over 100 different realizations is reported in Fig. 5. It is possible to find a curve that aims at an arbitrarily low residual error \( E^{*}_r \), by intersecting said surface with the horizontal plane with corresponding height. We set \( E^{*}_r = 0 \) obtaining the curve in Fig. 6.

The resulting relation \( C_r(P_l) \) has been stored in a Look-Up Table (LUT) as reported in the flow chart in Fig. 4

B. Frame Quality Selection

In our ALJC scheme the transmitter exploits feedback from the receiver to estimate the network throughput and packet loss. Once this has been done, the transmitter can compute the best viable value \( Q \) of the source coder, an integer in the \([0, 100]\) interval, where 0 denotes the highest compression rate, thus smallest image size and worst quality. In order to do this, the transmitter needs to know the relation between the parameter \( Q \) and the size of the obtained frame. Unfortunately,
due to the nature of the intra-frame lossy coding, it is not possible to find a closed form relation. For this reason, we averaged many different sequences obtained by compressing a raw sequence using varying $Q$ parameter and, for each, we averaged the resulting frame size $F_s$. The obtained computed relation represents the expected frame size resulting from each $Q$ parameter. It can be inverted to provide the $Q$ value to be used when aiming for a given frame size thus giving a curve which provides a value which represents the expected perceived quality for each frame portion is given by (1).

$$SSIM'(x, y) = \frac{(2\mu_x\mu_y + c_1) + (2\sigma_{xy} + c_2)}{(\mu^2_x + \mu^2_y + c_1)(\sigma^2_x + \sigma^2_y + c_2)}$$

(1)

$x$ and $y$ are the two small image blocks, $\mu_i$ is the $i$-th block pixel value average, $c_1$, $c_2$ are regularization terms, and $\sigma_i$ is the $i$-th block pixel standard deviation, $\sigma_{ij}$ is the quantity in (2),

$$\sigma_{ij} = \frac{1}{U-1} \sum_{k=1}^{V} (i_k - \mu_i)(j_k - \mu_j)$$

(2)

where $U$ is the number of pixels contained in the portion and $V$ is the overall number of portions.

To build a QoE model as a function of varying $Q$ parameter we averaged many different sequences obtained by compressing a raw sequence using varying $Q$ parameter and, for each, we averaged the resulting SSIM index. In this way we obtained a curve which provides a value which represents the expected perceived quality for each $Q$ choice (Fig. 8). Such relation is stored in a Look-Up Table (LUT) as reported in the flow chart in Fig. 4.

The $Q$ parameter controls several internal parameters of the JPEG source coder, and although it provides an intuitive scale of the quality of the compressed picture, it does not explicitly address the issue of how a frame will be perceived by an observer. For the same reason, although the mere maximization of $Q$ would allow the maximization of the QoE, without a better knowledge of the relation between $Q$ and the perceived QoE we cannot efficiently tackle problems of maximization with metrics such as fairness and/or efficiency of resource exploitation.

### C. Quality Metric

In order to be able to measure and maximize the QoE the Structural SIMilarity (SSIM) index is employed. SSIM [24] provides a measure of similarity between two images, where one is considered as “reference”. Its purpose is the same as the one of PSNR, but SSIM is devised to mirror how our visual system works, i.e., an SSIM score lies closer to the Mean Opinion Score (MOS).

As reported in [12], here reported for the sake of completeness, SSIM is computed over small portions of a frame, and the whole frame index $SSIM(f_i, f_i)$ between two frames $f_i$ and $f_i$ is obtained by averaging the individual portion values. The SSIM value for a single frame portion is given by (1).

$$SSIM'(x, y) = \frac{(2\mu_x\mu_y + c_1) + (2\sigma_{xy} + c_2)}{(\mu^2_x + \mu^2_y + c_1)(\sigma^2_x + \sigma^2_y + c_2)}$$

(1)

$x$ and $y$ are the two small image blocks, $\mu_i$ is the $i$-th block pixel value average, $c_1$, $c_2$ are regularization terms, and $\sigma_i$ is the $i$-th block pixel standard deviation, $\sigma_{ij}$ is the quantity in (2),

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The MOP theory, suited for the considered competitive situation, requires continuous, derivable and convex functions. Although the relation in Fig. 8 is discrete, $SSIM(Q)$ can be fitted with the function reported in Fig. 9.
Such red curve, called $SSIM_e(Q)$ is analytically expressed as a linear combination of exponential functions as reported in (3)

$$SSIM_e(Q) = ae^{bx} + ce^{dx}$$

Coefficients and exponents, obtained through the Minimum Squared Error method, are $a = 0.9207$, $b = 0.0007755$, $c = -0.4304$ and $d = -0.1483$. Finally, being convenient to employ convex functions in the MOP framework, the expected perceived quality (QoE) will be represented, in the Transmission Rate Allocation problem formalized in Section IV, by the function $f_{SSIM}(Q) = SSIM_e(Q)$. This function must be minimized to obtain the maximum QoE and the best QoE is reached when $f_{SSIM}(Q) \to -1$.

IV. Transmission Rate Allocation (TRA)

The aim of the TRA algorithm is to allocate the overall available transmission rate $R_{TOT}$ to the $Z$ considered source-destination paths as shown in Figure 3, maximizing fairness and average QoE, and reacting to channel variations: assuming that the TRA entity has some kind of channel state information available (e.g., the SNR), it can infer the experienced packet loss $P_l$ and thus, exploiting his knowledge of ALJC schemes: the expected quality parameter and channel code rates each transmitter is using. Since ALJC transmitters act with the aim to maintain a goal reference frame rate (set to 20 [frame/sec] in this paper), in order to maximize the QoE of each path we aim at minimizing each individual expected $f_{SSIM}(Q)$. To describe the TRA algorithm, we introduce some preliminary definitions:

$$R = (R_1, \ldots, R_Z)$$
$$C_r = (C_{r_1}, \ldots, C_{r_Z})$$
$$Q(R, C_r) = (Q(R_1, C_{r_1}), \ldots, Q(R_Z, C_{r_Z}))$$
$$F_{SSIM}(Q) = (f_{SSIM}(Q(R_1, C_{r_1})), \ldots, f_{SSIM}(Q(R_Z, C_{r_Z})))$$

In (4), vectors $R$ and $C_r$ contain respectively the transmission rates allocated to each source-destination path and the expected coderates employed by ALJC transmitters. $Q(R, C_r)$ is the vector of the values of the expected $Q$ parameter for each path, given the transmission rate and the channel code rate, and finally, $f_{SSIM}(Q(R_Z, C_{r_Z}))$ represents the expected perceived quality (i.e., QoE). As previously said, TRA aims to maximize the average QoE: this can be achieved by simultaneously minimizing every component of $F_{SSIM}(Q)$ defined in (4). Specifically, the allocation problem is formulated using the Multi Objective Programming (MOP) theory [21] applied in many fields such as in [25] and, similarly to this paper, in [26]:

$$\begin{align*}
& \min_{R_1, \ldots, R_Z} \left( f_{SSIM}(Q_1(R_1, C_{r_1})), \ldots, f_{SSIM}(Q_Z(R_Z, C_{r_Z})) \right) \\
& \text{with } R_z \in [0, R_{TOT}], \forall z \in [1, Z] \\
& \text{subject to } \sum_z R_z \leq R_{TOT}, R_z \geq 0 \forall z \in [1, Z]
\end{align*}$$

Each component of $F_{SSIM}$ is monotonically decreasing with the allocated transmission rate. Minimizing $f_{SSIM}$ means to try to allocate all the rate necessary to obtain $f_{SSIM} = -1$ for each path ($\forall z \in [1, Z]$). This solution is non-achievable if the sum of the necessary transmission rates exceed $R_{TOT}$. As a matter of fact, in this scenario, all paths compete with each other to obtain the resource; for this reason, in order to solve the problem defined in (5) it is necessary to pick a solution which represents a compromise, i.e., a Pareto Optimal Point (POP), in the minimization of each components of the vector $F_{SSIM}(Q)$.

The aforementioned compromise (POP) solution, whose existence is guaranteed because the MOP problem in (5) is convex (i.e., the considered functions are convex and the domain of the problem is a convex metric space, see [21] for details) can be obtained by reformulating the problem as $L_p$: this method selects a point within the feasibility region (defined by the problem constraints (5) $\sum_z R_z \leq R_{TOT}$, $R_z \geq 0 \forall z \in [1, Z]$) which minimizes the distance (i.e., $p$-norm) from a selected reference point. In this work we solve (5) and we define the reference point as $\mathbf{F}_{SSIM}^d = (f_{SSIM_{1}}, \ldots, f_{SSIM_{2}}, \ldots, f_{SSIM_{Z}})$, with $f_{SSIM_{z}} = -1 \forall z \in [1, Z]$. The rate allocation algorithm is thus formalized as an $L_p$-problem in (6):

$$\begin{align*}
R_{opt} &= \arg \min_{R_1, \ldots, R_Z} \| F_{SSIM}(Q(R, C_r)) - F_{SSIM}^d \|_p = \\
&= \arg \min_{R_1, \ldots, R_Z} \sum_z \left( |f_{SSIM}(Q(R_z, C_{r_z})) + 1|^p \right)^\frac{1}{p} \\
&\text{subject to } \sum_z R_z \leq R_{TOT}, R_z \geq 0 \forall z \in [1, Z]
\end{align*}$$

The optimal vector, $R_{opt} = (R_{opt}^1, \ldots, R_{opt}^Z)$ enumerates the transmission rates allocated to each link. This vector

- belongs to the feasibility region, that means that the sum of its components respects the overall available transmission rate $R_{TOT}$ constraint, and
• minimizes the distance, computed applying the generic $p$ norm, from the ideal vector $F_{SSIM}^{id}$.

V. EXPERIMENTAL RESULTS

We tested the proposed approach in various scenarios in which a number of transmitters want to stream their video to a corresponding receiver. Recalling Fig. 3, we consider a source and a destination for each video stream. We define path as the logical entity comprising

- a transmitter
- its corresponding receiver
- the logical link that enables communication between the two

The total available bandwidth on the gateway (GW in Fig. 1) is allocated in shares to the multiple paths. If no TRA policy is employed, such shares are equal (namely $\frac{\text{Prox}}{Z}$ each). Otherwise, if the TRA is enabled, the shares are computed dynamically as a function of the path loss each receiver is experiencing, which enables the TRA entity to exploit its knowledge of ALJC and estimate the coderate employed by the transmitter and the receiver QoE to be expected.

A. Testbed

a) Network: The testbed employs the mininet [27] framework to provide a set of network namespaces, each of which implements a network node. The typical network topology of our reference scenario consists in $Z$ transmitter nodes, $Z$ receiver nodes and a further namespace representing the satellite link.

b) Transmitter and Receiver: The functionalities of transmitters and receivers are implemented through Java application running on the network namespaces of the nodes. While the receivers provide proper feedback and stores the received video frames, the transmitter reads from a video file the frames to be sent. At the same time, it is able to employ the ALJC algorithm to dynamically control its source and channel coders.

c) TRA: The gateway node GW is controlled by a script, which sets the parameters emulating the packet loss rates of each logical link and is able to perform TRA and compute the optimal $R$ allocation through a C++ application implementing dynamic programming minimization.

B. Scenarios

We assume the transition from good to lossy channel conditions to be instantaneous, and in all our tests, whose overall duration is 100 [s], we set the transition to happen at $t = 30$ [s]. The considered scenarios are the following:

1) Two paths, one of which experiences moderate packet loss (Fig. 10)
2) Two paths, one of which experiences heavy packet loss (Fig. 11)
3) Four paths, one of which experiences heavy packet loss (Fig. 12)
4) Four paths, two of which experience heavy packet loss (Fig. 13)

For each of the above mentioned scenarios we report figures representing the SSIM index of each video frame as a function of time, with and without the TRA. We furthermore consider two figures of merit to compare results and quantify the benefits: the average SSIM experienced by a receiver throughout an emulation and the standard deviation among the various average experienced SSIM. While the first can be used to measure the QoE, the latter represents a measure of the fairness of the resource exploitation, i.e., an ideally perfect allocation would allow equally maximum QoE among the various receivers, resulting in 0 standard deviation.

C. Results

In scenario 1, a 15% packet loss is introduced in one of two the paths (path 0): since it does not represent a dramatic value, ALJC is able to protect the video stream adequately without TRA, resulting in a slightly lower individual average SSIM with respect to path 1 (0.8833 vs. 0.9406). The introduction of TRA of course equalizes the two results (Fig. 10). Since the packet loss is moderate, the gain is not enormous in terms of global average SSIM: in this sense, the adoption of TRA resulted in only a minor improvement (+0.66 %, see TABLE I). However, the fairness in how QoE is distributed is noticeably better, standard deviation goes from 0.04502 to 0.017.

Scenario 2 (Fig. 11) showcases the benefits of TRA much more evidently. Here path 0 experiences a high packet loss (30%), which causes the average per-path SSIM to fall to 0.7528 in path 0, while the non-lossy path 1 remains at 0.9392. The adoption of TRA actually succeeds in the original intent that drove our investigation, that is to exploit the strong non-linear behaviour of the source coding R-D curve. Here we can note a 5% improve in the average global SSIM (TABLE I).

In Scenario 3 only path 0 experiences heavy (30%) packet loss: in this case it benefits from a higher number of “giving” paths. Because three out of four paths are fairly stable (they experience high quality with and without the employment of TRA), and thus only path 0 is significantly affected, the change in the global average SSIM is modest although positive. However, the fairness of the QoE is strongly improved, as can be graphically seen from the SSIM curves (Fig. 12).

By introducing heavy packet loss in two out of four path (Scenario 4, Fig. 13) we can note how the employment of TRA results in a significant increase in QoE fairness, thus driving the global average SSIM lower than in Scenario 3 because there are now two paths that need to be granted extra resource. However, if compared to a uniform (without TRA) allocation, it nonetheless allows a moderate improvement (+0.9%, TABLE I).

All results are summarized in TABLE I.

To sum up, in all cases we observed that, in addition to ALJC, the TRA allows a much higher fairness. As the TRA operating principle is to move some percentage of resource from good state paths to impaired ones, we can see that greater fairness gains can be expected (e.g., Fig. 12) whenever there are many paths able to “donate”.
**Packet Loss**

\[ t = 0 \quad t = 30s \]

**No TRA**

\[
\begin{array}{c|c|c}
\text{path 0} & 0\% & 15\% \\
\text{path 1} & 0\% & 0\% \\
\end{array}
\]

\[
\begin{array}{c|c|c}
\text{path 0} & 30\% & 0\% \\
\text{path 1} & 0\% & 0\% \\
\end{array}
\]

**Fig. 10.** Two paths, one experiences moderate packet loss

**Packet Loss**

\[ t = 0 \quad t = 30s \]

**No TRA**

\[
\begin{array}{c|c|c}
\text{path 0} & 0\% & 30\% \\
\text{path 1} & 0\% & 0\% \\
\text{path 2} & 0\% & 0\% \\
\text{path 3} & 0\% & 0\% \\
\end{array}
\]

\[
\begin{array}{c|c|c}
\text{path 0} & 30\% & 0\% \\
\text{path 1} & 0\% & 0\% \\
\text{path 2} & 0\% & 0\% \\
\end{array}
\]

**Fig. 11.** Two paths, one experiences heavy packet loss

**Packet Loss**

\[ t = 0 \quad t = 30s \]

**No TRA**

\[
\begin{array}{c|c|c}
\text{path 0} & 0\% & 30\% \\
\text{path 1} & 0\% & 0\% \\
\text{path 2} & 0\% & 0\% \\
\text{path 3} & 0\% & 0\% \\
\end{array}
\]

\[
\begin{array}{c|c|c}
\text{path 0} & 30\% & 0\% \\
\text{path 1} & 0\% & 0\% \\
\text{path 2} & 0\% & 0\% \\
\end{array}
\]

**Fig. 12.** Four paths, one experiences heavy packet loss

**Packet Loss**

\[ t = 0 \quad t = 30s \]

**No TRA**

\[
\begin{array}{c|c|c}
\text{path 0} & 0\% & 30\% \\
\text{path 1} & 0\% & 0\% \\
\text{path 2} & 0\% & 0\% \\
\text{path 3} & 0\% & 0\% \\
\end{array}
\]

\[
\begin{array}{c|c|c}
\text{path 0} & 30\% & 0\% \\
\text{path 1} & 0\% & 0\% \\
\text{path 2} & 0\% & 0\% \\
\end{array}
\]

**Fig. 13.** Four paths, two experience heavy packet loss

**CONCLUSIONS**

We refer to scenarios where multiple video streams need to be transmitted over a shared resource, with each potentially ex-
TABLE I
OBSERVED QUALITY (SSIM) AND FAIRNESS (STANDARD DEVIATION σ )
GAINS, EXPRESSED AS PERCENTAGE VARIATIONS OBTAINED WHEN USING
TRA WITH RESPECT TO THE NON-TRA CASE.

<table>
<thead>
<tr>
<th>Case</th>
<th>SSIM gains (% = path with packet loss)</th>
<th>Fairness (σ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>path 0</td>
<td>+2.55%</td>
<td>-1.1%</td>
</tr>
<tr>
<td>path 1</td>
<td>+15.76%</td>
<td>-2.71%</td>
</tr>
<tr>
<td>path 2</td>
<td>+13.25%</td>
<td>-2.94%</td>
</tr>
<tr>
<td>path 3</td>
<td>+6.36%</td>
<td>-2.60%</td>
</tr>
<tr>
<td>global avg.</td>
<td>+6.61%</td>
<td>-3.80%</td>
</tr>
</tbody>
</table>

Experiencing different link conditions and where the employment
of an application layer adaptive joint coding algorithm (called
ALJC) allows to benefit from an increased rate allocation. We
propose the introduction of a centralized resource allocation
mechanism (called TRA), which, exploiting feedback from the
multiple link conditions and a-priori knowledge of the adaptive
coding, allows a better (in terms of experienced quality) and
more fair QoE (i.e., ideally all video streams are experienced
with equal quality). We implemented each element of the
mentioned scenario and ran emulations to prove the concept
and show the obtained benefits.

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