A Comparison Between ULP and MDC With Many Descriptions for Image Transmission

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***Abstract*—In this letter, we present a performance comparison between multiple description coding (MDC) and unequal loss protection (ULP) for progressive image transmission over lossy packet networks. Two optimization criteria are considered, i.e., a multi-quality criterion, when N distinct quality levels are guaranteed at the decoder side, and the optimization of the expected quality at the receiver. We resort to both a semi-analytical approach and simulation results. To enable numerical comparisons, we address a specific MDC algorithm suitable for progressive imaging, and a state-of-the-art ULP algorithm based on Reed Solomon codes. The results, although cannot be generalized to any MDC and ULP methods, are useful to put into evidence some general features that can drive the selection of the most proper technique for the application at hand. In fact, they allow to put into evidence the main advantages and drawbacks of either technique.**

***Index Terms*—Error resilience, graceful degradation, JPEG 2000, multiple description coding (MDC), unequal loss protection (ULP).**

I. Introduction

IN modern communication networks, users may want to download or stream multimedia data using heterogeneous terminals. The contents may be accessed using broadband networks such as domain-specific languages (DSLs), optical cable or WiMax, but also full mobility GPRS/UMTS or beyond 3G networks. In this context, layered source coding is a valuable tool. However, when packets are built on top of a layered source, the loss of a lower layer prevents one from exploiting the subsequent ones. On the other hand, in bandwidth-demanding applications, it is of paramount importance to be able to exploit all the received packets at the application level. Two popular tools achieving this objective are multiple description coding (MDC) and unequal loss protection (ULP).

In MDC [1], nonhierarchical representations of the source are generated, yielding mutually refinable information, whereas in ULP, erasure correcting codes with different rates are applied to data layers, so as to enable the decoding of more important layers with higher probability. In this case, at least $k_{\min}$ descriptions should be received to decode the basic quality level, with $k_{\min}/N$ being the rate of the most powerful channel code employed. The main difference between MDC and ULP is that the former is traditionally conceived to generate few descriptions (in most cases, only two of them), whereas ULP generates many descriptions. Moreover, the quality achieved by ULP does not depend on which descriptions have been received, but only on their number. In general, this feature is not guaranteed in MDC [2].

This letter provides a comparison between the two approaches, applied to the transmission of progressively encoded images over packet lossy networks. This comparison is not trivial because, whereas the basic principles of ULP are well established, many diverse MDC methods have been proposed. We deem that, to achieve sensible comparisons with ULP, MDC should exhibit these main features: efficiency and flexibility in the redundancy insertion and exploitation; possibility of achieving many ($N > 2$) descriptions, so that several quality levels can be imposed by both ULP and MDC. Moreover, we restrict ourselves to algorithms yielding balanced streams that are compliant with standard tools such as JPEG-MPEG co-decoders. Finally, computational complexity should also be taken into account, even though this is beyond the scope of this letter, and is left to future investigation.

MD scalar quantization (MDSQ) [3] has been used for image coding in [4]–[6]. However, MDSQ can hardly be generalized to $N > 2$, and yields descriptions that are not standard-compliant streams. Similarly, methods that make use of pairwise correlating transforms [7] or lapped transforms for image and video [8] are difficult to generalize to $N > 2$, and yield descriptions that cannot be decoded with standard tools. In [9], two JPEG 2000 streams are generated, at rates R_1 and $R_2 < R_1$, and two balanced descriptions are obtained by merging codeblocks encoded at either rate. The scheme has been generalized to $N > 2$ in [10]. In [2] a similar algorithm is proposed to achieve N descriptions from a memoryless Gaussian source encoded at N rate values.

The ULP methods proposed so far all implement the concept of priority encoded transmission, i.e., allocating more powerful codes to more important data layers. They address different code families and code optimization strategies. The basic framework is presented in [11], whereas in [12] a practical optimization algorithm is presented, where the rates of Reed-Solomon (RS) codes are obtained so as to maximize the expected performance at the receiver. The same algorithm is applied in [13], where it is recognized that ULP is very sensitive to variations of the estimated packet loss rate. A cross-layer control mechanism is implemented so as to make the optimization task aware of the actual network conditions, even though the complexity of the optimization task is likely to prevent this mechanism from working in real time.

From this brief discussion, it can be noticed that few MDC algorithms are suitable for a sensible comparison with ULP. Nevertheless, some effort in this direction has already been

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spent. In [14], a comparison between MDC and FEC is presented, using a memoryless Gaussian source and addressing rate-distortion (RD) performance bounds. The authors come to the conclusion that MDC outperforms ULP in case delay constraints are present, and a feedback is available on the channel conditions. However, the generalization of such results to real-world data is not trivial, as MDC performance bounds are known not to be strict [15]. In [16], [17], a joint application of source channel coding and scalable MDC is proposed. From the reported results, worked out using Gaussian data, one can infer that methods using channel coding generally outperform MDC in matched transmission conditions. However, the situation may be different if this condition is not satisfied.

In this letter, we consider a multiquality optimization criterion, i.e., that N distinct quality levels are guaranteed at the receiver side. We develop a semi-analytic approach to work out the rate required by either technique to achieve the same quality levels. In order to put this formulation into practice, we tailored the *rate-distortion (RD)-aware MDC* (RMDC) method proposed in [2] to appropriately address the JPEG 2000 codec. This algorithm is reported to yield good performance; the redundancy can be easily tuned by means of a simple parameter; it allows for any number of descriptions; it provides an analytical formulation of the distortion terms; it allows to generate balanced descriptions. However, in its original formulation, RMDC does not support JPEG 2000 data. Moreover, no analytical formulation was given to work out the algorithm parameters (namely, the encoding rates) under the multiquality criterion. In this letter, we properly modify the algorithm in [2] so that it can handle JPEG 2000 data and can be optimized under the multiquality criterion. Even though the main goal of this letter is to enable sensible comparison between ULP and a suitable MDC method, the presented performance results related to RMDC, working under the multiquality criterion, are indeed novel. As for ULP, we employ the framework of [11], which performs unequal allocation of Reed-Solomon (RS) codes to data fragments obtained from a progressive source, and similarly to [12] and [13], we assume that ideal erasure codes of rates i/N, $i = 1, \dots, N$ are available. The code rates are obtained so as to achieve the objective at hand. Then, we provide simulation results referring to MDC and ULP when they are designed so as to optimize the expected quality at the receiver side for given packet loss rate and source RD characteristics, and when they are designed to guarantee a given number of quality levels at the receiver side.

II. The RMDC Algorithm

RMDC [2] defines $N!$ data subsets $\mathbf{S}_l,\ \ l = 1, \dots, N!$, which are balanced in the RD sense. Then, a vector $\mathbf{R}$ of N monotonically decreasing rates $R_j,\ j = 1, \dots, N$ is worked out as the optimization result. Subset $\mathbf{S}_1$ is encoded along descriptions using a permutation π_1 of $\mathbf{R}$, and so on for subset $\mathbf{S}_2\ (\pi_2), \dots, \mathbf{S}_{N!}\ (\pi_{(N!)})$. Hence, no subset is encoded at the same rate in two distinct descriptions. The rate devoted to each description is $R_d = 1/N \sum_{j=1}^{N} R_j$.

At the decoder side, all the received descriptions are merged into a single bitstream, where, for each subset, the finest representation is retained. The distortion terms when k descriptions out of N are received are given by [2]

$$d_{k,N} = \frac{k(N-k)!}{N!} \sum_{j=1}^{N-k+1} \frac{(N-j)!}{(N-k-j+1)!} f(R_j) \qquad (1)$$

where $d = f(r)$ is the data RD function. This function is evaluated in state of the art encoders, such as JPEG 2000, and can be directly obtained from such encoders. If all the descriptions are received, the representation at the best possible quality (i.e., at rate R_1) is available for each subset. Thus, the central quality of this scheme is given by the RD curve at rate R_1, and the redundancy is $\rho = N \cdot R_d - R_1$. Even though in [2] the scheme is only validated for Gaussian data, it can be adapted to JPEG 2000 data, considering code-blocks (CBs) as the data subsets. In this case, it is necessary to identify CB subsets that are equivalent from the RD standpoint. Even though explicit RD evaluation and exact CB classification is possible, for the sake of simplicity here we resort to a static CB pattern allocation. We assume that, for each level of DWT decomposition, the CBs belonging to each subband can be simply split into the descriptions, according to a permutations of the rate vector $\mathbf{R}$. It is worth noticing that this assumption does not impact on the system RD performance, but can induce a slight imbalance among descriptions.

III. Multiquality Criterion

In order to make sensible comparisons between MDC and ULP, it is necessary that they undergo the same optimization criterion. A sensible approach is to guarantee a given number N of quality levels at the receiver side (*multiquality criterion*). It is suitable e.g., for multiple-tree P2P streaming protocols [18], where each peer is responsible for the delivery of a single data thread.

Let us work out a semi-analytical formulation of the total rate requested by ULP and MDC while guaranteeing the same quality levels. Let us consider ULP first. We assume using ideal erasure codes, whose rates are i/N, $i = 1, \dots, N$. We deal with a progressive source, which is divided into N layers. R'_i is the cumulative rate devoted to encode the first i layers, $i = 1, \dots, N$. If all code rates are used, then each layer will contribute to the quality improvement; this makes ULP fully compatible with the MDC paradigm. The total rate necessary to encode the data can be worked out as

$$\begin{aligned} R_{ULP} &= N \sum_{i=1}^{N-1} \frac{R'_i}{i(i+1)} + R'_N \\ &= N \sum_{i=1}^{N-1} \frac{f^{-1}(d_{i,N})}{i(i+1)} + f^{-1}(d_{N,N}) \end{aligned} \qquad (2)$$

with $d_{i,N}$ being the distortion when decoding the first i data segments (i.e., the first i layers). Hence, it is possible to impose N quality layers, determined by distortions $d_{i,N}$, $i = 1, \dots, N$, and evaluate the rate necessary to guarantee them.

Let us now consider the case of MDC yielding N balanced descriptions. The total required rate is $R_{MD} = N \cdot R_d$ with R_d being the rate devoted to each description. When i out of N descriptions are received, amounting to a rate $i \cdot R_d$, a distortion $d_{i,N}$ is obtained independent of the subset of received descriptions, if a fully balanced MDC scheme is adopted. The relationship of this distortion with R_d depends on the algorithm at hand. Hence, from this point on it is necessary to consider a particular MDC algorithm, to set the same N quality levels as in ULP, to work out R_d necessary to achieve such distortions, and finally to work out the total rate. Here, and as said before, we consider RMDC, but we emphasize that any other MDC method, for which the distortion terms are analytically known and that allows to have fair comparison with ULP, can be used instead.

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TABLE I
R_{ULP} AND R_{MD} [BPP]. N UNIFORM QUALITY LEVELS: LENA IMAGE

range	30 to 40 dB				20 to 40 dB			
N	4	8	12	16	4	8	12	16
R_{MD}	1.26	1.71	2.14	2.58	1.04	1.17	1.26	1.34
R_{ULP}	1.46	2.09	2.64	3.15	1.08	1.25	1.37	1.46

For the RMDC scheme, it is possible to evaluate the rate vector $\mathbf{R} = \{R_j : j = 1, \ldots, N\}$ that guarantees N quality levels, by recursively using the expression [from (1)] [1] shown in (3), shown at the bottom of the page, for $j = 1, \ldots, N-1$, and $R_1 = f^{-1}\{d_{N,N}\}$. The total rate required by the RMDC can be evaluated as $R_{MD} = \sum_{j=1}^{N} R_j$.

In order to compare both approaches, we used the JPEG 2000 codec engine from the OpenJPEG libraries [19]. The DWT with (9,7) filter bank and four decomposition levels is addressed. The Lenna image of dimension 512×512 pixels is used; similar results, not reported for brevity, hold for different images. Table I reports the total rates R_{ULP} and R_{MD} in bits per pixel. Both schemes have been tuned so as to deliver N equi-spaced quality levels in the range $[20, 40]$ dB and $[30, 40]$ dB. The reported results reveal that RMDC yields lower rates than ULP. This can be interpreted considering that, in this situation, ULP introduces a large coding redundancy, as the decoding of only one description (or very few descriptions) require the use of very low rate codes. It is worth noticing that the higher rate values of the configuration $[30, 40]$ dB dB, is due to the more stringent quality requirements with respect to the configuration $[20, 40]$ dB.

IV. Maximization of the Expected PSNR Criterion

The goal in this section is to compare ULP and RMDC, designed so as to maximize the expected PSNR at the decoder side. In this situation, a semi-analytical performance assessment is impractical. Hence, we resort to simulations, and evaluate the performance of the two systems when all users are subject to the same description loss rate p. It is worth noticing that in [12], the code allocation is designed so as to maximize the expected PSNR. As for RMDC, the expected PSNR is optimized for static p in [2]. Hence, such algorithms can be fairly compared. Fig. 1 reports the expected PSNR achieved by RMDC and ULP, as a function of the description loss rate p and for several values of N, for the image Lenna encoded at a total output rate $R_t = 1.2$ bits per pixel (bpp), and header information is accounted for in the total rate. We can notice that for $N = 4$, the two methods are equivalent, whereas when $N > 4$, ULP significantly outperforms RMDC.

The performance of RMDC is almost independent of N for $N \geq 8$. This can be explained noticing that increasing N implies replicating the JPEG 2000 header information and this latter is far from negligible. In the case of Lenna 512×512, $R_t = 1.2$ bpp and several values of p, we have verified that the performance saturates for $N \geq 8$. ULP methods are not affected by such a phenomenon since they do not require JPEG 2000 header duplication because this latter is part of the most significant layer.

[1]See also www.telematica.polito.it/sas-ipl/download.php for the proof.

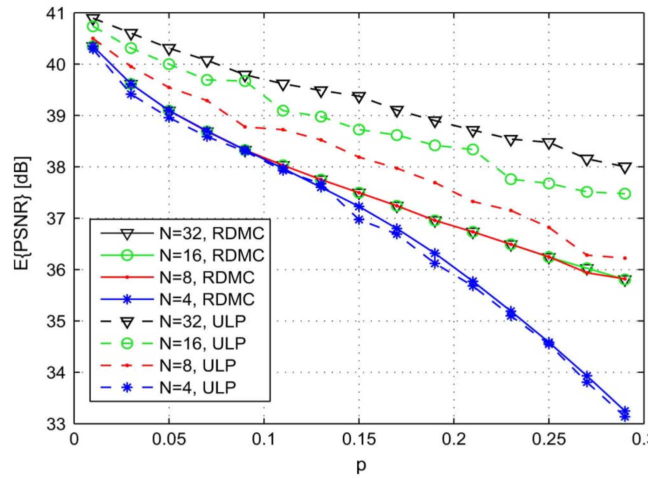

Fig. 1. Expected PSNR (dB) versus description loss rate: RMDC and ULP.

The fact that ULP outperforms RMDC for $N > 4$ can be explained considering two aspects. From one hand, the ULP algorithm in [12] is tailored for the case of many descriptions (the original paper addresses $N = 16$). From the other hand, the way redundancy is inserted in RMDC makes it suitable for few descriptions. In fact, only the CBs encoded at the highest available rate are retained, whereas the others are simply discarded. Moreover, as already discussed, header information has been accounted for in order to assure that the descriptions are JPEG2000-compliant streams; this has not been imposed to ULP. The joint effect of header duplication and replicated information in the multiple CB encoding, makes RMDC suboptimal for large values of N as for the expected PSNR.

More insight can be gained considering the behavior when not all the data are received. Fig. 2 reports the PSNR as a function of η, the percentage of received data, $N = 8$ and several p values. When all data are received, both algorithms yield the same PSNR, revealing that they allocate the same amount of redundancy. However, they differ in the way redundancy is exploited. The performance of RMDC increases gracefully with η. For example, when $p = 0.17$, each further description received achieves a PSNR gain of about 2.5 dB, and $N = 8$ different quality levels are enable at the receiver. $\mathrm{PSNR} = 30$ dB is reached when 3 descriptions are received (37.5% of data). On the other hand, ULP exhibits the cliff phenomenon typical of FEC-based methods. As a matter of fact, this reveals a strong dependency of its performance on the correctness of p, which may be detrimental in highly nonstationary environments. In fact, if the design value of p is underestimated, it is likely that less data than expected is received, and this can yield a significant quality

$$R_{j+1} = f^{-1}\left\{\binom{N}{N-j} d_{N-j,N} - \frac{1}{(N-j-1)!} \sum_{k=1}^{j} \frac{(N-k)!f(R_k)}{(j-k+1)!}\right\} \tag{3}$$

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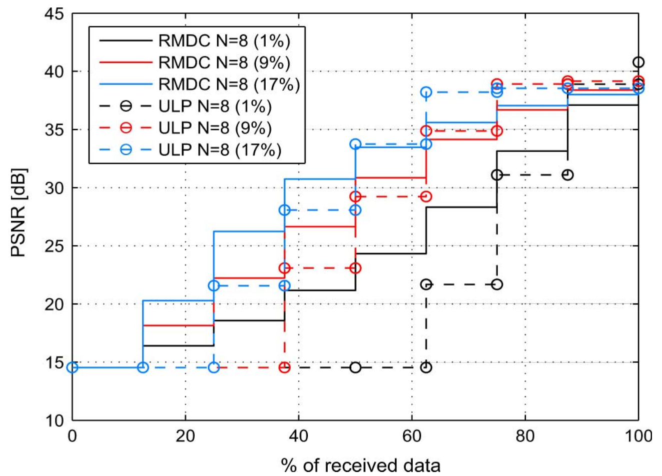

Fig. 2. PSNR (dB) versus percentage of received data: RMDC and ULP, $N = 8$.

drop. This behavior is more evident for p values as low as 0.01. In this case, ULP allows for four quality levels, and the coarsest one, corresponding to $\mathrm{PSNR} \approx 22$ dB, requires the reception of 62.5% of data; $\mathrm{PSNR} = 30$ dB is reached with six descriptions received (75% of data).

Similar considerations, not reported for brevity, hold for $N = 32$. RMDC yields 32 quality levels, and the reception of a further description yields a PSNR improvement of 0.78 dB on average. On the other hand, ULP yields a variable number of quality levels (8 for $p = 0.17$, 4 for $p = 0.01$), and exhibits a steeper behavior. If the design p is 0.17 (0.01, respectively), the threshold $\mathrm{PSNR} = 30$ dB is achieved when about 60% (90%) of data are received.

V. Conclusions

In this letter, we presented a performance comparison of the RMDC algorithm in [2] with ULP based on RS code allocation. When both algorithms are designed so as to yield N distinct quality levels, RMDC outperforms ULP as for the total required rate. On the other hand, when the two algorithms are optimized in terms of the expected PSNR at the receiver side, ULP outperforms RMDC as for the expected PSNR, whereas RMDC exhibits graceful degradation performance to a larger extent and is more tolerant to variations of the p parameter. Such results, even though they cannot be simply generalized to any MDC and ULP scheme, put into evidence some features that can be considered general, e.g., the presence of cliff effects in ULP and the strict dependency of its performance on the estimation of p. On the other hand, being based on consolidated FEC code theory, the optimization in terms of the expected PSNR given p is more effective in ULP than in MDC. Further developments can be in the direction of extending the performance comparison under the multiquality criterion to other MDC techniques, for which an analytical formulation of the distortion terms is available. Moreover, the computational complexity should also be taken into account, whereas for the algorithms addressed in this letter, MDC is definitely less complex than ULP; using codes with lower decoding complexity than RS (e.g., Raptor Codes) could modify this perspective. This topic is left to future developments.

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