TRANSMISSION DISTORTION-OPTIMIZED UNEQUAL LOSS PROTECTION FOR VIDEO TRANSMISSION OVER PACKET ERASURE CHANNELS

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ABSTRACT

In this paper, we study the problem of Transmission Distortion-optimized Unequal Loss Protection (TD-ULP) under rate constraints for non-scalable video transmission over packet erasure channels. Based on a packet-level transmission distortion modeling scheme, we estimate the amount of contribution of each video packet to the reconstructed video quality, which defines the priority level of each packet. Unequal amounts of protections are then allocated to different video packets according to their priority levels as well as the dynamic channel conditions. The optimal ULP resource allocation is formulated as a constrained nonlinear optimization problem. An evolutionary algorithm based on Particle Swarm Optimization (PSO) is developed to obtain the optimal resource allocation. Our extensive experimental results demonstrate the effectiveness of the proposed TD-ULP scheme, which outperforms existing methods by up to 2dB gain in reconstructed video quality.

Index Terms—resource allocation, Unequal Loss Protection (ULP), transmission distortion model, Particle Swarm Optimization (PSO)

1. INTRODUCTION

Robust transmission of compressed video over unreliable networks has emerged as an active and challenging area of research. Within the current best-effort based packet-switched networks, how to efficiently allocate limited communication resources for video transmission while providing desirable Quality of Service (QoS) remains a challenging problem.

A variety of error-resilient techniques have been proposed to minimize video quality degradation due to transmission errors [1]. Among these techniques, Unequal Loss Protection (ULP) has been proven to be very promising to solve this problem by taking advantage of the differential importance of packets in encoded video bit streams. The idea is to allocate more resources to the parts of the video sequence that have a greater impact on video quality, while spending less resource on the parts that are less significant.

Different types or positions of video frames in a Group-Of-Pictures (GOP) have been explored for unequal loss protection for non-scalable video transmission over packet erasure channels. The seminal work, Priority Encoding Transmission (PET), proposed by Leicher and Albanese [2, 3], allows a user to set different priorities of error protection for different frames in a GOP, which however didn't provide any explicit algorithm for the optimal allocation of protection. F. Hartanto proposed an FEC assignment scheme, which empirically assigns FEC to I-frames and P-frames with fixed protection ratios by treating all P-frames equally [4], thus the temporal dependencies among P-frame in a GOP is not exploited [5]. To address this problem, Yang *et al.* considered the non-stationary distributed importance of the frames in a GOP by formulating the impact of packet loss and error propagation on the video quality degradation as an expected length of error propagation (ELEP), and then a local hill-climbing algorithm is used to search for the optimal ULP assignment [5].

While there is a significant body of research on ULP to improve performance of video transmission systems, few of them have considered video content and find optimal solutions for the problem. For those that did consider video content, they only provide a coarse-level content-aware ULP, because they mainly operate on frame level or video layer level rather than at packet level. We observe that packet-level transmission distortion model and priority scheduling play a key role in unequal loss protection. In addition, in existing work, the issue of unsuccessfully decoded BOP (Block of Packets) has not been adequately addressed.

The main contributions of this paper are three-fold. First, a predictive transmission distortion model is introduced to accurately characterize the importance level of each packet, which serves as the basis of our transmission distortion-optimized ULP method. Second, a close-form formulation of unequal loss protection for video transmission over packet erasure channels, which jointly considers packet distortions and dynamic channel conditions, is proposed. When a BOP cannot be decoded successfully, the contributions of those video packets in the BOP to the reconstructed video are explicitly considered. Third, an evolutionary optimization algorithm based on particle

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swarm optimization is developed to solve the constrained nonlinear optimization problem and obtain the optimal resource allocation.

The rest of the paper is organized as follows. Section 2 overviews the system framework, followed by the transmission distortion modeling and channel modeling. Then, the transmission distortion-optimized ULP problem is formulated as a constrained nonlinear optimization problem and particle swarm optimization is used to solve the problem. The performance of the proposed TD-ULP algorithm is evaluated in Section 3, and Section 4 concludes the paper.

2. PROPOSED TD-ULP SCHEME

2.1. System Overview

Fig. 1 shows the system diagram of the proposed transmission-distortion optimized ULP scheme.

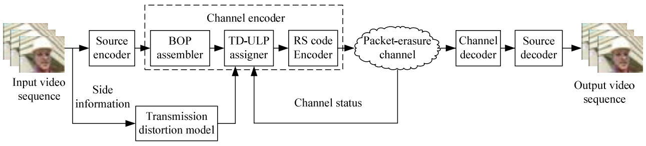

Fig. 1. System overview

Raw video are first compressed by a source encoder, during which the side information including the instantaneous transmission distortion and motion reference ratio [6] are extracted and fed to the transmission model to predict the transmission distortion of each packet, which will be elaborated in the next subsection. Encoded video packets of a GOP are assembled into several BOPs using the BOP assembler. The two-state Markov model is utilized as the channel model and to estimate the packet loss rate after channel decoding. More details will be presented in Subsection 2.3. Based on the transmission distortion of each video packet and the channel status, the TD-ULP assigner module allocates limited channel bit rate budget to different packets such that the end-to-end distortion is minimized. Subsection 2.4 formulates the optimal ULP allocation as a constrained optimization problem and Particle Swarm Optimization is used to solve the problem and find the best ULP assignment in Subsection 2.5. Video packets are then protected by RS codes across packets with obtained channel coding parameters. Fig. 2 depicts the BOP structure for a GOP and the RS codes across packets. More specifically, for the j-th BOP with K_j source video packets, $NS(N_j, K_j)$ ($N_j \geq K_j$) code is applied across the K_j source video packets and F_j FEC packets are generated to form total N_j packets. The BOP can be successfully decoded with any K_j packets out of the N_j packets being correctly received.

2.2. Transmission Distortion Modeling

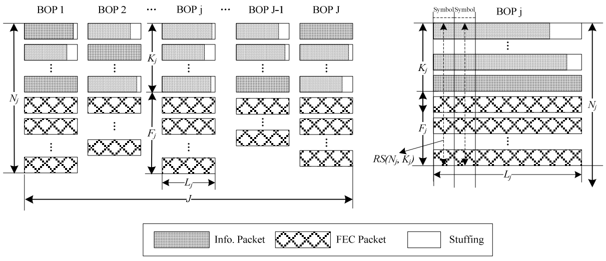

Fig. 2. (l) Illustration of unequal FEC protection assignment, (r) FEC across BOP j with $NS(N_j, K_j)$

A simple yet accurate transmission distortion model has been proposed in [6], which enables us to accurately predict at the encoder side the corresponding distortion or video quality degradation at the decoder side if a packet is lost. In this model, the transmission distortion of each MB (Macro Block) D_t can be estimated as:

$$D_t = D_0 \times (M + 1) \qquad (1)$$

where D_0 is the instantaneous transmission distortion after error concealment in the frame where the lost packet locates and M denotes the motion reference ratio, both of which are byproduct of the encoder and can be extracted after video encoding. More details of this model can be found in [6].

Fig. 3. MBs are of unequal importance: (*Foreman*: frame 2-5)

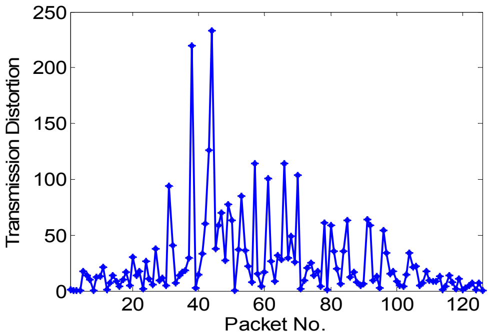

Fig. 4. Different packets are of unequal importance (*Foreman*)

With this model, the transmission distortion of each MB can be easily obtained before channel coding. Examples are shown in Fig. 3. As expected, MBs in different frames exhibit quite different transmission distortion. Given a specific packetization scheme, the unequal importance of each packet can then be derived as the sum of the transmission distortion of the MBs within it. Examples of the transmission distortion of each packet are depicted in Fig. 4. This predicted transmission distortion will later serve as the basis of the transmission distortion-optimized ULP assignment.

2.3. Channel Modeling

The two-state Markov model [7] has been widely used to model the packet loss for the Internet or wireless fading channels [5, 8]. The two states of the model are denoted as G (good) and B (bad), as shown in Fig. 4. In state G packets are received correctly and timely whereas in state B packets are lost.

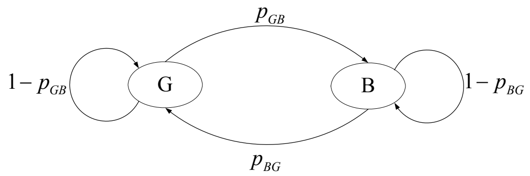

Fig. 5. Two-state Markov model

The channel statistics of the model is described by two parameters: the average packet loss rate P_B and the average burst length L_B, which can be obtained by feedback information of the underlying protocols such as the Real time Control Protocol (RTCP) [9]. Based on P_B and L_B, the associated transition probability p_{BG} from the state B to G and p_{GB} from state G to B can be easily computed as:

$$p_{BG}=\frac{1}{L_B},\quad p_{GB}=\frac{p_B}{L_B(1-p_B)} \tag{2}$$

Let $g(v)$ denote the probability that a loss-free interval length is $v-1$, i.e., $g(v)=P_r(0^{v-1}1\,|\,1)$, where "1" denotes a lost packet and 0^{v-1} denotes $v-1$ consecutive successfully received packets. Similarly, let $G(v)$ denote the probability of the a loss-free interval length is greater than $v-1$, i.e., $G(v)=P_r(0^{v-1}\,|\,1)$. Thus, we have [8]

$$g(v)=\begin{cases}1-P_{BG}, & v=1\\ P_{BG}(1-P_{GB})^{v-2}P_{GB}, & v>1\end{cases} \tag{3}$$

$$G(v)=\begin{cases}1, & v=1\\ P_{BG}(1-P_{GB})^{v-2}, & v>1\end{cases} \tag{4}$$

Let $R(n,k)$ be the probability of $k-1$ packet losses with the next $n-1$ packets following a lost packet, it can be calculated as the recurrence

$$R(n,k)=\begin{cases}G(n), & k=1\\ \sum_{v=1}^{n-k+1}g(v)R(n-v,k-1), & 2\le k\le n\end{cases} \tag{5}$$

Then the probability of k lost packets within a block of n packets can be computed as [7, 8]

$$P(n,k)=\sum_{v=1}^{n-k+1}P_B G(v)R(n-v+1,k),\ 1\le k\le n \tag{6}$$

2.4. Problem Formulation

Assuming that a total bit budget R_T has been allocated to a GOP with source rate R_S, then the amount of channel rate left for FEC is $R_C=R_T-R_S$. With this total amount of bit rate, we aim to find the optimal resource allocation policy $\vec{F}$ ($\vec{F}=\{F_1,F_2,F_3,\ldots,F_J\}$), which achieves the best quality of reconstructed video with the presence of packet loss.

Given the above analysis, the problem of finding the optimal ULP allocation problem can be formulated as a constrained nonlinear optimization problem which maximizes the reconstructed video quality at the receiver side, i.e., minimizes the end-to-end distortion, subject to the rate constraints, as follows [5, 8, 9]

$$\begin{aligned}&\min_{\vec{F}} D(\vec{F})=\sum_{j=1}^{J}D_j\cdot P_R(N_j,K_j)\\ &s.t.\quad R_C(\vec{F})\le R_T-R_S\end{aligned} \tag{7}$$

where D_j is the distortion of the j-th BOP and can be computed as the sum of the transmission distortion of the packets in this BOP with $D_{ji}, i=1,2,\ldots,K_j$ denoting the transmission distortion of the i-th packet in BOP j

$$D_j=\sum_{i}^{K_j}D_{ji}. \tag{8}$$

P_R denotes the residual packet loss rate after FEC decoding. In case of a $RS(N_j,K_j)$ code, P_R, which is the probability of more than N_j-K_j packets are lost within a BOP, can be computed as

$$P_R=\sum_{k=N_j-K_j+1}^{N_j}P(N_j,k) \tag{9}$$

And the channel rate R_c is computed as

$$R_C(\vec{F})=\sum_{j=1}^{J}(F_j\times L_j)\times F_r\,/\,G_s \tag{10}$$

with F_r being the frame rate in frame per second and G_s being the GOP size. The length of the FEC packet in j-th BOP L_j is determined by

$$L_j=\max_{i=1,2,\ldots,K_j}\{L_{i,j}\} \tag{11}$$

where $L_{i,j}$ is the length of the i-th video packet in BOP j.

The above problem formulation is derived based on the property that for a BOP protected by a $RS(N_j,K_j)$ code, this BOP cannot be decoded successfully when more than N_j-K_j packets are lost within a BOP. However, the correctly received video packets within this unsuccessfully decoded BOP are still useful for decoding which are however discarded and considered as lost in existing methods [5, 8, 9]. In other words, the distortion will be enlarged and thus the formulation is inaccurate, which may lead to a sub-optimal ULP allocation.

In the following, we study the expected distortion with the useful information packets in the unsuccessfully decoded BOPs being taken into consideration. For the j-th BOP protected by $RS(N_j,K_j)$ code, the BOP is decodable and no distortion is introduced when no more than $F_j=N_j-K_j$ packets are lost. When the number of lost packets exceeds F_j, say $F_j+m(1\le m\le K_j)$ packets out of the total N_j packets within BOP j are lost with the probability of $P(N_j, F_j+m)$, the BOP cannot be decoded successfully, and on average, $\frac{F_j+m}{N_j} * K_j$ packets out of the K_j video packets are lost and the rest are still useful for decoding. The expected distortion for BOP j can be computed as

$$\begin{aligned} E(D_{BOP_j}) &= \sum_{m=1}^{K_j} \frac{F_j+m}{N_j} \cdot K_j \cdot \frac{D_j}{K_j} \cdot P(N_j, F_j+m) \\ &= \sum_{m=1}^{K_j} \frac{F_j+m}{N_j} D_j \cdot P(N_j, F_j+m) \end{aligned} \tag{12}$$

Thus, the problem in (7) can be reformulated as

$$\begin{aligned} \min_{\vec{F}} E[D(\vec{F})] &= \sum_{j=1}^{J} \sum_{m=1}^{K_j} \left(\frac{F_j+m}{N_j} D_j \cdot P(N_j, F_j+m) \right) \\ \text{s.t.} \quad & R_C(\vec{F}) \le R_T - R_S \end{aligned} \tag{13}$$

2.5. PSO-based Resource Allocation and ULP

Searching for the global optimal solution for the constrained nonlinear optimization problem formulated in previous section is computationally intensive, if not prohibitive, in a practical system, especially when the length of the GOP and the number of packets in a GOP increase. Local hill-climbing [5, 10], local search [11], convex-hull-based algorithm [12], Lagrangian-based algorithm [13] or Genetic Algorithm (GA) [14] have been used to solve this problem. However, they either requires the convexity, or are too computational complex, or easy to fall into the local optima or has many algorithm parameters to tune.

Particle swarm optimization (PSO) [15] is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. The attractive features of PSO, including the ease of implementation, no gradient information is required, and no evolution operators such as crossover and mutation as in GA and fewer parameters to adjust when compared to GA [16], has made it a very promising candidate to solve this problem. Thus, in this paper, we utilize PSO to solve this problem and achieve the optimal ULP assignment.

In PSO, each particle is associated with a position and a velocity, which are dynamically adjusted towards its historical best position $p_i(t)$ and the global best position $p_g(t)$ that all particles have found so far

$$\begin{aligned} V_i(t+1) &= w(t)V_i(t) + c_1 r_1 (p_i(t) - x_i(t)) + c_2 r_2 (p_g(t) - x_i(t)) \\ x_i(t+1) &= x_i(t) + V_i(t+1) \end{aligned} \tag{14}$$

where $x_i(t)$ is the current position of individual i at iteration t, with $V_i(t)$ satisfies $V_{\min}(t) \le V_i(t) \le V_{\max}(t)$. $w(t)$ is the inertia weight factor, while c_1 and c_2 are acceleration constants and r_1 and r_2 are random variables with a uniform distribution, respectively. Therefore, the particles track optimum points to search the space and find the optimal solution.

When applying PSO to obtain the optimal ULP allocation, each solution, i.e., an ULP assignment, is represented by a particle, and the whole flock of particles fly through the search space and converge to the most promising regions, i.e., the objective function in (13).

To tailor the original real-value PSO for the combinational optimization problem of optimal ULP allocation, the positions of each particle is updated as in (14) and rounded to the nearest integer in each generation [17].

A penalty function is used to handle the constraint and convert the constrained problem of (13) to

$$\min_{\vec{F}} J(\vec{F}) = D(\vec{F}) + f_P(\lambda, \vec{F}) \tag{15}$$

where the penalty function is defined as

$$f_P(\lambda, \vec{F}) = \lambda_1 \left| (R_T - R_S) - R_C(\vec{F}) \right| \tag{16}$$

with λ being the penalty factor reflecting the degree of constraint violation, which is chosen in such a manner that it allows the PSO to converge to the optima very fast at the beginning by initially a small penalty factor and then refines the solution by increasing the penalty factor.

Now, by solving the problem in (15), the optimal solution for the problem of (13) can be obtained. The PSO-based solution is summarized in Algorithm 1.

Algorithm 1 PSO-based solution for TD-ULP problem

```
Input: video information and channel status.
Output: optimal ULP allocation $\vec{F}$ .
For each particle
    Initialize each particle according to the ELP assignment;
    Initialize the particle's best known position $p_i(0)$ to its initial position ;
    Initialize the particle's velocity $V_i(0)$ ;
End For
Update the swarm's global best fitness value $p_g(0)$ ;
While maximum iterations or minimum error criteria is not met Do
    For each particle
        Calculate the fitness value as in (15);
        If the fitness value is better than the best fitness value in history of particle $i$ , i.e., $p_i(t)$ ;
            Set current value as the new $p_i(t)$ ;
    End For
    Choose the particle with the best fitness value of all the particles as the global best fitness value $p_g(t)$ ;
    For each particle
        Update particle's velocity and position according to (14);
        Round the position of each particle to the nearest integer;
    End For
End Do
```

3. PERFORMANCE EVALUATION

In this section, we first evaluate the PSO-based solution for the optimum resource allocation problem and the performance of the proposed transmission distortion-optimized ULP algorithm is then evaluated.

Test video sequences in QCIF size, *Mother&Daughter*, *Foreman* and *Coastguard*, are encoded by MPEG-4 and the video packets are protected by RS code with parameters obtained in the previous section. All packets, either the original video packets or FEC packets, are transmitted over the two-state Markov model-simulated packets erasure channel, and the experimental results were averaged over 50 lossy channel transmission realizations.

3.1. PSO-based Resource Allocation for ULP

This section demonstrates the PSO-based solution for the above formulated constrained optimization problem. Fig. 6 shows the convergence of the fitness function on the left and each of the variables on the right. As can be seen, the PSO-based solution converges very quickly.

Fig. 7 shows the optimal ULP allocation result with PSO. The transmission distortion of the BOPs within the 2nd GOP for *Mother&Daughter* sequence is plotted on the left. As we can see, packets in BOPs 2-5 are having higher importance levels than others, among which packets in BOP 3 are the most important. Intuitively, more FEC protections should be assigned to these packets and packets in BOP 3 deserve the strongest FEC protection. The right plot shows the optimal ULP allocation result by PSO with average packet loss rate being 20%, average burst length being 3 and FEC ratio 20%, which perfectly matches our intuitive guess.

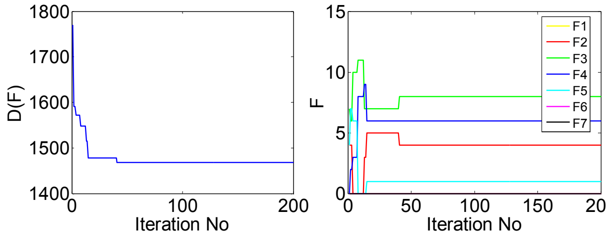

Fig. 6. Convergence of the objective value and ULP allocation

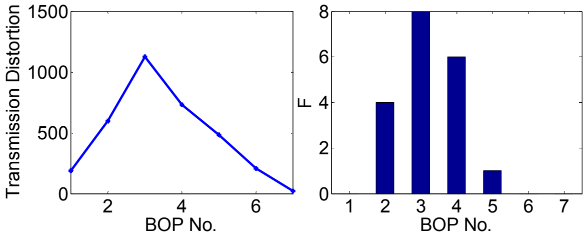

Fig. 7. Optimal ULP allocation result by PSO

3.2. Performance Evaluation and Comparison

The effectiveness of the proposed TD-ULP scheme is validated with a wide range of packet loss rates and FEC ratios. Table I lists the experimental parameters.

For comparison purpose, we also implemented the ELEP-based ULP schemes proposed in [5], denoted as ELEP_ULP, as well as the Equal Loss Protection (ELP) which treats all the packets equal and provides them the same level of protection. Besides, when searching for the optimal resource allocation, the local hill-climbing algorithm used in [5] will likely fall into the local optima. For the fairness of comparison, the PSO algorithm is used to obtain the optimal ULP assignment for both ULP schemes.

Table I. Experimental Parameters

Source coding parameters	
Encoder	MPEG-4
Total frames	90
GOP length	15
Frame rate	30fps
Packet length	1280bits
Channel parameter	
P_B	5%~20%
L_B	3~5 packets
Channel coding parameters	
FEC ratio	5%~20%
BOP size K	20 packets

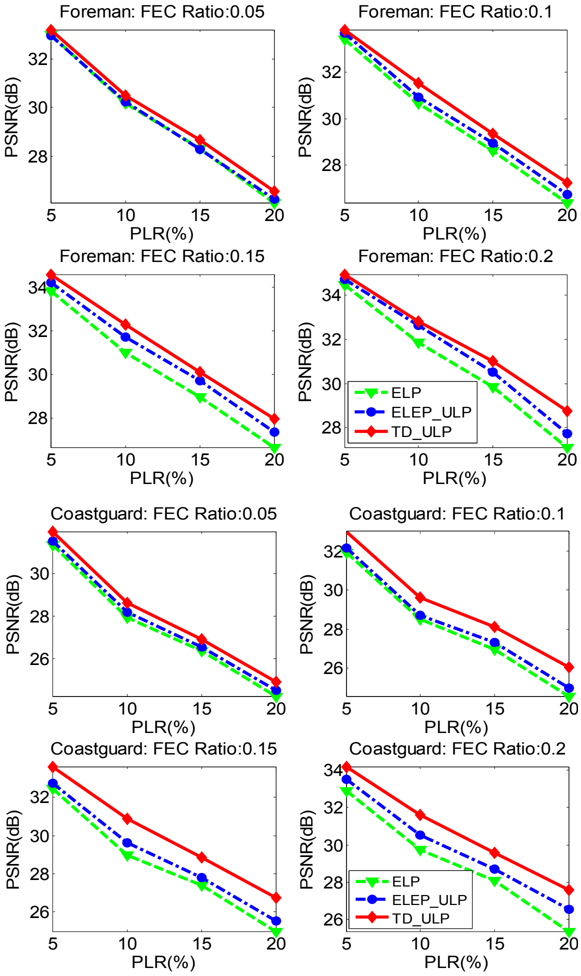
Foreman: FEC Ratio:0.05
Foreman: FEC Ratio:0.1
Foreman: FEC Ratio:0.15
Foreman: FEC Ratio:0.2
Coastguard: FEC Ratio:0.05
Coastguard: FEC Ratio:0.1
Coastguard: FEC Ratio:0.15
Coastguard: FEC Ratio:0.2

Fig. 8. Comparison of reconstructed video quality for test video sequences *Foreman* and *Coastguard* with average packet loss rate (PLR) ranging from 5% to 20%, average burst length fixed to 3, BOP size K=20 and the FEC ratio from 5% to 20%, respectively.

Fig. 8 shows the reconstructed video quality at the receiver side for *Foreman* and *Coastguard* sequences, respectively, with packet loss rate and FEC ratio ranging from 5% to 20% while the average burst length being fixed to 3 packets. As we can see, our proposed TD-ULP scheme consistently outperforms the other two schemes, while

Yang's ULP scheme performs better than the ELP scheme. On average, a video quality improvement of about 0.5-1dB is achieved when comparing with Yang's ELEP_ULP scheme and an improvement up to 2 dB is achieved when comparing with the ELP method.

The performance of the proposed TD-ULP scheme is also evaluated with different average burst lengths of the lossy channel with comparison against ELP and ELEP_ULP, and the result for *Mother&Daughter* sequence is listed in Table II. Again, our proposed TD-ULP scheme consistently outperforms the other two schemes. Experiments on other test video sequences yield similar results.

Table II Reconstructed video quality under different average burst lengths with p_B =20% and FEC Ratio=20%

LBs	ELP	ELEP_ULP	TD_ULP
3	31.0780	32.0760	**32.7133**
4	30.1109	31.0573	**31.9895**
5	29.7384	30.5600	**31.7095**

The above performance comparisons are based on the objective evaluation of the reconstructed video quality in PSNR. We will also show some subjective results of the reconstructed video frame from the simulation runs. Fig. 9 shows snapshots of the 70th frame for *Coastguard* with average packet loss rate 20%, FEC ratio 20%, average burst length 3 and BOP size K=20, respectively. We can see that TD-ULP algorithm can provide improved subjective visual quality compared to the other two schemes, especially those areas with rich content and high motion, like the ship area.

(a) ELP (b) ELEP_ULP (c) Proposed TD_ULP.

Fig. 9. Subjective quality comparison.

4. CONCLUSIONS

In this paper, we proposed a transmission distortion-optimized unequal loss protection TD-ULP scheme. A close-form solution of the distortion-optimized resource allocation for unequal loss protection was developed based on the transmission distortion of each video packet, where the contribution of correctly received source video packets in unsuccessfully decoded BOP are explicitly considered when formulating the optimization problem. An evolutionary algorithm based on Particle Swarm Optimization was then developed to solve the formulated constrained nonlinear optimization problem and obtain the optimal ULP assignment. Our extensive experimental results demonstrated the effectiveness of the proposed TD-ULP scheme, which outperforms existing methods by up to 2dB gain in reconstructed video quality.

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