NO-REFERENCE METRICS FOR VIDEO STREAMING APPLICATIONS

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ABSTRACT

In this paper[1] we present no-reference metrics to evaluate the following two major distortions in streaming of compressed video over packet-switched networks: i) block-edge impairment and ii) the effect of packet loss. The first metric proposed measures block-edge impairments in reconstructed video frames and is based on the idea that these impairments are best observed in regions with low spatial activity. The second metric proposed in this paper evaluates distortion in reconstructed video frames due to packet loss by exploiting the structure of the artifact. Both metrics have low computational complexity and can be used for real-time monitoring of streaming video in a multimedia transmission scenario. Further these measures could be used as feedback to help a streaming server perform dynamic rate adaptation or dynamic selection of scalable video streams in case of increasing network congestion.

1. INTRODUCTION

In today's world of multimedia communication over lossy networks like best-effort IP networks, it is crucial to be able to monitor the effects of compression- and transmission-related distortions in order to quantify the users Quality of Experience (QoE). QoE relates the actual quality as perceived by an end-user to the overall communication system's Quality of Service (QoS). Due to the nature of streaming media, quality monitoring has to be conducted in real-time, and a reference stream for quality comparison is most often not available. Thus one requires a *No-Reference* (NR) metric with the ability to estimate the end-user's experience of a multimedia presentation without using an original audiovisual media stream as reference.

This paper deals with monitoring the quality of streaming video by quantifying distortions introduced by compression and transmission over lossy packet-switched networks. For IP networks, the deterioration in perceived quality is typically due to packet loss[1, 2].

In the current best-effort Internet service model, no service guarantees with respect to packet loss, delay jitter and available bandwidth can be made. Packet loss most often occurs due to congestion in network nodes; more and more packets are dropped by routers in IP networks when congestion increases. While packet loss is one of the things that make the TCP protocol efficient and fair for non-real-time applications communicating over IP networks, the effect of packet loss is a major issue for real-time applications such as streaming of audiovisual media using the RTP protocol over UDP/IP. Even delay jitter manifests itself as packet loss, since packets received after the intended play-out/presentation time are not useful.

The other major source of distortion and degradation of perceptual quality in multimedia communication is because of the inevitable coding and compression of media sources. In particular, for block-based video compression schemes such as the ISO/IEC and ITU standards (e.g. MPEG-1/2/4, H-261/3/4) the main forms of distortions include block impairment effects, blurring, ringing and the DCT basis image effect [3, 4]. NR metrics that has been proposed, in general try to quantify the effects of these distortions [5, 6] but the emphasis of research on NR metrics has been predominantly on quantifying the effects of block impairment artifacts [7, 8, 9, 10]. This is because, block impairment artifacts tend to be perceptually the most significant of all coding artifacts [7]. With the Video Quality Experts Group (VQEG) working towards their standardization [11], NR metrics remain a topic of great research interest.

In this paper, we present two novel NR metrics, one to measure block edge impairments (or blockiness) in compressed video and the other to measure the effectiveness of concealment strategies that try to mitigate the effects of packet loss on the overall video frame quality. The blockiness metric is based on measuring the activity around the block edges and on counting the number of blocks that might contribute to the overall perception of blockiness in the video frame while the effect of packet loss is measured by ex-

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ploiting the structural pattern of this artifact. These metrics could be used for monitoring the quality of streaming video as well as being part of a feedback mechanism to assist in adapting the delivery of streaming video to varying network conditions.

Section 2 presents related work, while section 3 presents the basic ideas underlying the block edge impairment metric and describes how it is computed for each reconstructed frame. Section 4 describes the metric evaluating the effect of packet loss. Results and discussion are presented in section 5. Finally, section 6 concludes the paper.

2. RELATED WORK

Algorithms to measure block edge impairments (blockiness) have used a variety of methods to do so. Wang and Bovik proposed an algorithm based on taking the FFT along the rows and columns of block boundaries to estimate the strength of the block edges while Vlachos used cross-correlation of subsampled images to compute a blockiness metric [8]. Wu and Yuen proposed a metric based on computing gradients along block boundaries while tempering the result with a weighing function based on the human visual system (HVS) [7]. The computations yielded a number for each frame that represented the block edge strength for that frame. Similar ideas about the HVS were utilized by Suthaharan [12] and Gao et al.,[10]. The general idea behind these metrics was to temper the block edge gradient with the masking activity measured around it. This approach utilizes the fact that the gradient at a block edge can be masked by spatially active areas around it, and the fact that this distortion is masked well in very dark or bright regions [4]. Several of these approaches have proven to be quite effective but can be computationally quite complex for real-time implementation.

Boyce et al., [2] studied the effect of how MPEG video transmission over IP affect the received video quality. Though they have discussed the effects of packet loss over various frame types, no quantitative measure have been proposed for measuring the perceptual effect in reconstructed video. Verscheure [13] et al., have analyzed the relation between the perceived quality to the encoding bit-rate for MPEG-2 video. Further they show how the PSNR measure is not reliable for measuring video quality. Their final conclusion indicates that the image quality can not be improved by acting on the coding bit rate alone. Kimura et al., [14] addressed the issue of creating layers to maximize the perceived quality of video over a given range of network conditions. They used the perceptual distortion metric (PDM) proposed by Winkler [15], which is a general HVS based distortion metric. As this is a Full-Reference (FR) metric using the original video frame as the reference quality, it is not suitable for monitoring the quality as perceived by an end-user in streaming media applications. Feamster et al., [1] have analyzed the effect of packet loss on the quality of MPEG-4 video and proposed a model to explain these effects. An overview of several methods for post-processing based concealment of the effects of packet loss in video is presented in [16].

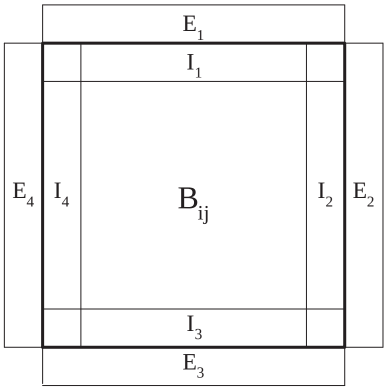


Fig. 1. An 8×8 block and its edges.

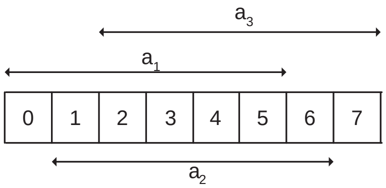


Fig. 2. Three segments a_{kl} of a block edge

3. PROPOSED NR BLOCKINESS METRIC

The metric proposed in this work is based on the idea that a block-edge gradient can be masked by a region of high spatial activity around it. It can be observed that block edge impairments perceived in a video frame is usually because of blocks with at least one edge exhibiting low activity. Let B_{ij} represent an 8×8 starting at location (i, j) in a given frame. I_k,$k = 1, \ldots, 4$ represents the edges of the block as shown in Figure 1.

To measure the activity along a given edge I_k we first divide it into three segments of length 6, namely, a_{k1}, a_{k2} and a_{k3}. This is shown in Figure 2.

$$\begin{aligned} a_{k1} &= I_k(n) : n = 0 \ldots, 5 \\ a_{k2} &= I_k(n) : n = 1 \ldots, 6 \\ a_{k3} &= I_k(n) : n = 2 \ldots, 7 \end{aligned} \quad (1)$$

We define activity as the standard deviation, σ_{kl} for each a_{kl}, and $l = 1, \ldots, 3$. For a given edge I_k, $k = 1, \ldots, 4$ activity is defined to be low if at least one of σ_{ki}, $l = 1, \ldots, 3$ is below a chosen threshold ε. In other words, if there is at least one segment of the edge which has low activity (standard deviation) then the edge and thus the block it belongs to can contribute to the overall perception of blockiness of the frame.

The metric is then computed as follows. For each frame:

1. Initialize the block counter $C_B = 0$.

2. In each block B_{ij} along each edge I_k, for each a_{kl}, $k = 1, \ldots, 4$ and $l = 1, \ldots, 3$ compute the standard deviation, σ_{kl}.Thus we obtain three activity measures per edge giving us a total of twelve activity measures.

3. Now compute the gradient corresponding to each a_{kl}

$$\begin{aligned} \Delta_{k1} &= \text{mean}|I_k(n) - E_k(n)| : n = 0 \ldots, 5 \\ \Delta_{k2} &= \text{mean}|I_k(n) - E_k(n)| : n = 1 \ldots, 6 \\ \Delta_{k3} &= \text{mean}|I_k(n) - E_k(n)| : n = 2 \ldots, 7 \end{aligned} \tag{2}$$

   where E_k, $k = 1, \ldots, 4$ are the edges adjacent to the corresponding block edges, E_k, $k = 1, \ldots, 4$, as shown in Figure 1.

4. If at least one segment satisfies

$$\begin{aligned} \sigma_{kl} &< \varepsilon \\ \Delta_{kl} &> \tau \end{aligned} \tag{3}$$

   $k = 1, \ldots, 4$ and $l = 1, \ldots, 3$, increment C_B by 1. That is, we count B_{ij} as contributing towards the overall perception of blockiness of the frame.

The overall blockiness measure $\mathcal{B}_F$ for the present frame, is then

$$\mathcal{B}_F = \frac{C_B}{\text{Total number of blocks in the frame}}. \tag{4}$$

Clearly, the range of the metric is $[0, 1]$ where a value of 0 corresponds to no visible block edge impairment, and increasing values of B_F implies increasing block edge impairments in reconstructed video frames.

The bit depth for the video sequence is assumed to be 8 bits or 255 gray-scale levels. The value of ε is chosen as a threshold to isolate edges with low activity. To this end we chose $\varepsilon = 0.1$. This corresponds to the situation when there is a minimal deviation from the mean of the segment. Increasing the value of ε would result in edges with a greater standard deviation being picked. This would mean picking blocks with segments that might have enough spatial activity to mask the block-edge gradient for that edge.

The value of τ can be chosen so that given low activity, the largest perceivable block-impaired edges will be counted in the metric. Increasing the value of τ would mean rejecting segments with low spatial activity which also have a block edge gradient that can be perceived. On the other hand, choosing a very small value of τ would result in a situation where an imperceptible edge might result in a block being counted, thus giving a false reading. For our simulations we chose a value of $\tau = 2.0$ because we found through our simulations that this value of τ performs better for wide range of video sequences.

4. PROPOSED NR PACKET LOSS METRIC

The loss of video packets often results in loss of slice information which in turn results in corruption of visual information along macroblock and slice edges. The decoder used in this work uses a simple temporal replacement algorithm for error concealment, where a damaged/lost macroblock is simply replaced by the corresponding macroblock from the previous frame. This causes a visible discontinuity when macroblock data from regions with considerable motion between consecutive frames are lost, as shown in Figs. 9 and 10. These structural distortions can be captured by checking the edges of the macroblock rows. The length of the artifact along the macroblock is proportional to the damage incurred by a slice. The metric proposed in this section measures the length of the artifact to estimate the distortion introduced in the given video frame caused by packet loss. At the same time it can estimate the efficacy of concealment strategies being used by the decoder. Note that while the concealment strategy used in the scenario under consideration here is simple, this metric can be applied to gauge the performance of more complex strategies which attempt a smoother concealment of packet loss artifacts. Indeed, it could be used to further refine concealment algorithms to mitigate packet loss related artifacts. To our knowledge, so far, no metric has been explicitly designed for this purpose.

4.1. MPEG-2 Transport Stream Packetization

In our experiments for measuring the effect of packet loss we consider MPEG-2 video streams. MPEG-2 specifies the following two systems: i) Program Stream (PS): multiplexed video, audio and data together form a PS which is meant for recording applications such as DVD, and ii) Transport Stream (TS): a packet-based format geared towards transmission (e.g. digital television). PS and TS are created from 18,800-byte segments of packetized elementary stream (PES) obtained from the source encoder.

The MPEG-2 video stream hierarchy consists of a sequence composed of three types of pictures namely, i) intra-coded (I), ii) predictive-coded (P) and iii) bidirectional (B) pictures. Each picture is composed of slices, which are comprised of one or more contiguous macroblocks. The macroblock is the basic coding unit, and is a 16×16 pixel segment in a frame. The macroblocks within a slice are ordered from left-to-right and top-to-bottom. Slices are important in the handling of errors. If the bitstream contains an error, the decoder can skip to the start of the next slice. Having more slices in the bitstream allows for better error detection and concealment, but introduces overhead that could otherwise be used to improve picture quality.

Due to entropy and differential coding, the data loss spreads within the frame till the next resynchronization point (*i.e.*, next picture or slice header). When loss occurs in a reference frame (I or P), the error propagates temporally due to motion compensation and predictive coding. The error concealment techniques may reduce the sensitivity of data loss to a certain level. Still, no satisfactory error concealment technique exists [16].

4.2. Proposed Approach

Consider an image frame of size $m \times n$ (height $\times$ width) and let R_i indicate the ith row of the frame. Now compute,

$$\begin{aligned} \hat{E}_j &= |(R_{(i-1)} - R_{(i+1)}) * P|, \qquad (5) \\ \hat{E'}_j &= |(R_{(i-2)} - R_i) * P|, \quad \text{for } i \in \{16, 32, \ldots, m-16\} \end{aligned}$$

Here, $*$ stands for convolution operation and $j = i/16$. $\hat{E}_j$, a row vector of length n, gives the edge strength across the macroblock rows j and $j+1$ while $\hat{E'}_j$ gives the edge strength very close to $\hat{E}_j$ within jth macroblock. Here, $P = [1,\ 1,\ 1]/3$ is a simple low-pass filter. Each row vector $\hat{E}_j$ and $\hat{E'}_j$ is then subjected to a threshold τ to give the final binary edges E_j and E'_j. In order to avoid the noisy edges and to pick-up the visible horizontal edges, the value of τ is set at 15 for all our experiments.

$$E_j(k) = \begin{cases} 1 & : \text{ if } \hat{E}_j(k) > \tau; k = 1, 2, \ldots, m \\ 0 & : \text{ otherwise} \end{cases} \qquad (6)$$

$$E'_j(k) = \begin{cases} 1 & : \text{ if } \hat{E'}_j(k) > \tau; k = 1, 2, \ldots, m \\ 0 & : \text{ otherwise} \end{cases}$$

Note that it is important to avoid including real edges in the video content while estimating the effect of packet loss. For this purpose the E'_j corresponding to the E_j under consideration is used. Because E_j and E'_j represents the edge maps of adjacent rows, they must have similar edges in a regular undistorted frame. This assumption is valid since all the images have smooth spatial edge continuity, and sharp edges in the original video content rarely are horizontally aligned with the macroblock boundary of a frame. Hence the effect of the packet loss artifact along the macroblock row j is computed as the difference between the edge maps E_j and E'_j. A small threshold ζ is used to avoid the effect of noisy edges. In our experiments the value of ζ is set as 10% of the maximum possible error (*i.e.*, 10% of frame width (n)).

The effect of packet loss for the jth macroblock row is now obtained as:

$$H_j = \begin{cases} \sum_i |E_j(i) - E'_j(i)| & : \text{ if } \sum_i |E_j(i) - E'_j(i)| > \zeta \\ 0 & : \text{ else, } j = 1 \ldots \frac{m}{16} - 1 \end{cases} \qquad (7)$$

H_j is thus a measure of the extent to which the edge of the slice is corrupted. The cumulative effect of H_j gives a packet loss metric for the whole frame. In our experiments the value of H_j is normalized to the range 0 to 1. The cumulative effect of packet loss for the current frame is then computed as,

$$F = \sum_j H_j^2 \qquad (8)$$

Since H_j lies between 0 and 1, H_j^2 tend to give more weightage to the higher value of H_j than lower ones. In other words, lengthier artifacts are given more weightage than shorter artifacts. Since this method exploits the structure of the artifact across the macroblock boundaries, the algorithm is computationally very economical.

5. SIMULATIONS AND RESULTS

In the following two subsections we describe the experimental setup and the results obtained for the proposed NR metrics.

5.1. NR blockiness metric

For our simulations we considered 10 sec. video sequences in CIF resolution (frame size of 352×288), 30 frames/sec and YUV (4:2:0) format. For results presented here we only consider the Y or the luminance channel. The original video sequence was encoded using the XviD MPEG-4 ASP codec [17] with a GOP size of 30 frames. The NR metric was computed for each frame of the original and the encoded sequence. Here we present results obtained for the "Mother-Daughter" and "Paris" sequences. We compare the performance of the proposed metric with the Wang, Sheik and Bovik (WSB) quality assessment model [9]. MATLAB code for the model was obtained from [18]. Because the WSB metric increases with better image quality and typically has range of 0 to 10, we normalize by 10 and subtract the result from 1. This procedure allows us to compare its performance with that of the proposed metric. Figure 3 show the result of applying the metric to the first two GOPs (frames 1-60) of the "Paris" sequence and Figure 4 shows the corresponding results for the WSB metric. Note that the proposed metric is nearly zero for the original sequence. In other words, it measures no blockiness in the uncompressed original video as expected. At the same time, we see that the metric increases as the compression increases or equivalently, the bit rate decreases. This is in keeping with the fact that higher compression implies coarser quantization

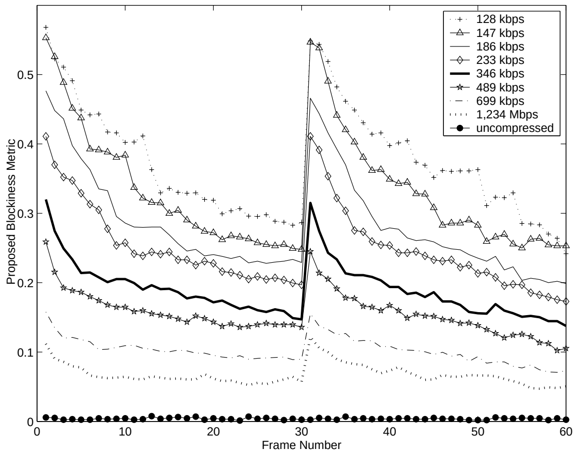


Fig. 3. Proposed blockiness metric for the first 60 frames of the ”Paris” sequence coded at different bitrates.

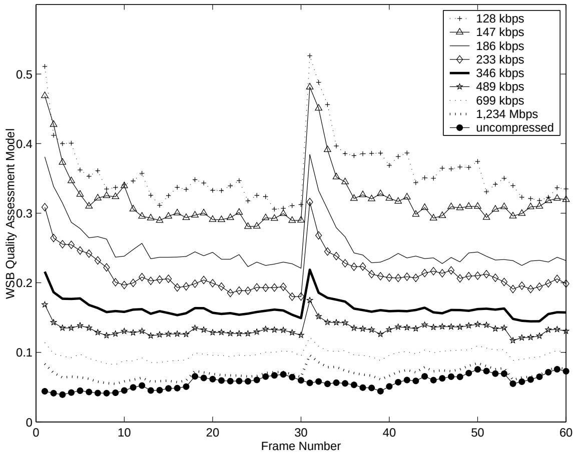


Fig. 4. WSB metric for the first 60 frames of the ”Paris” sequence coded at different bitrates.

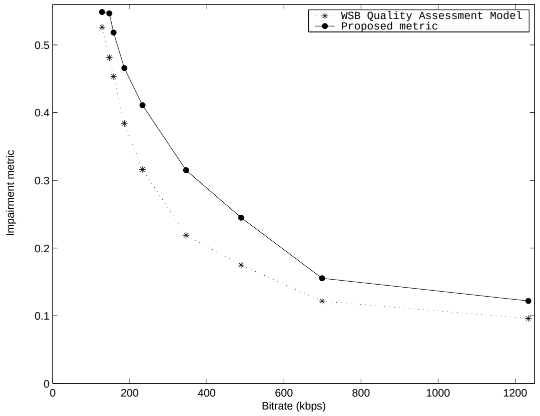


Fig. 5. Comparison of the proposed metric and the WSB metric for frame 31 of the ”Paris” sequence at different bitrates.

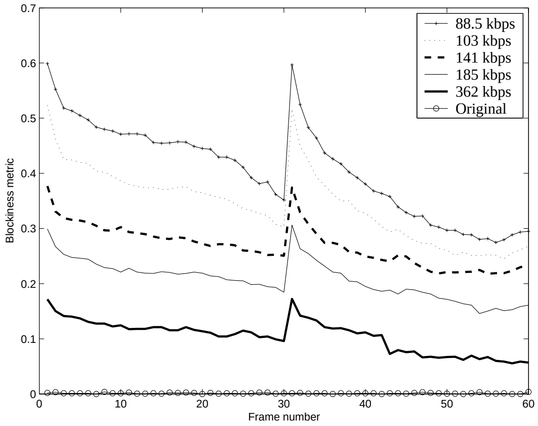


Fig. 6. Blockiness measurements for the first 60 frames of the ”Mother-Daughter” sequence coded at different bitrates.

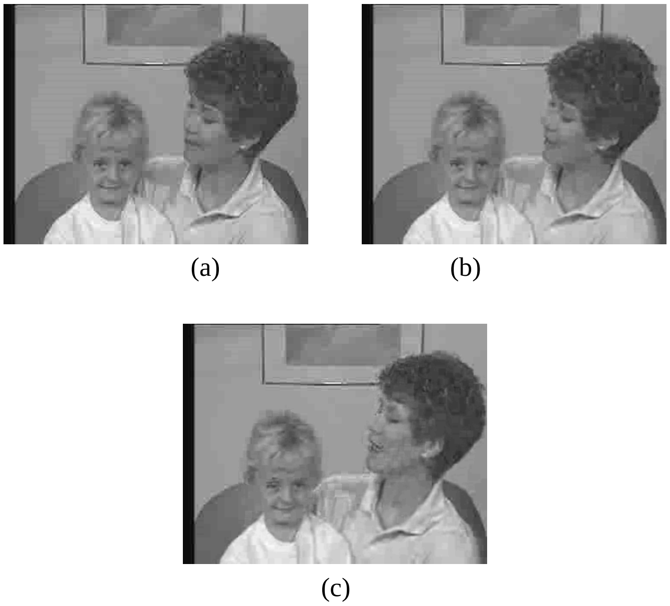
and consequently increased perceived block edge impairments. The peaks in the Figure indicates the I (intra coded) frame. The peak suggests that blockiness perceived in the I-frame is the highest in a GOP at all bit rates.

Figure 5 shows the change in both metrics for one frame, namely, frame number 31 which is an I (intra coded) frame encoded at different rates, namely, 1.234 Mbps, 699 kbps, 489 kbps, 346 kbps, 233 kbps, 186 kbps 147 kbps and 128 kbps. It can be seen that both curves show a graceful behavior, and that the measured block edge impairment decreases with increasing bitrates, as expected.

Figure 6 shows the performance of the proposed metric for the first 60 frames of the “Mother-Daughter” sequence. Again note that the metric is nearly zero for the original uncompressed video frame. Also note that the metric attains its maximum for frame number 31 which is the I-frame.

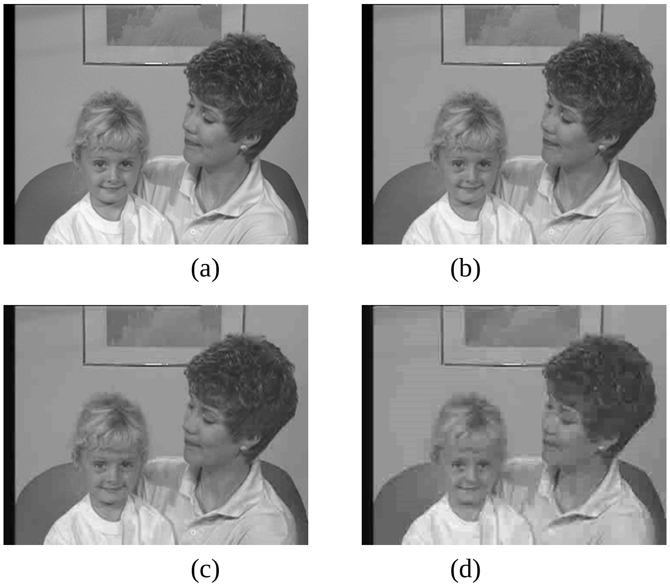
Figure 7, shows the frame 31 (I-frame), frame 40 and frame 55 for the “Mother-Daughter” sequence, encoded at 88.5 kbps. As the blockiness metric decreases from 0.62 for frame 31 in figure 7(a) to 0.28 for figure 7(c), we see that the blockiness perceived in these frames also decreases. In addition, note that other impairments such as blurriness and ringing start to play a part in the overall perception of the frame.

Figure 8 shows one frame, namely, frame number 31 which is an I (intracoded) frame encoded at three different rates, namely, 362.1 kbps, 141 kbps and 88.5 kbps, along with the original. The corresponding blockiness metrics are given in the caption to the figure. One can see substantial blockiness in the Figure 8(d). The corresponding value of the blockiness metric here is 0.62. Likewise, as the perceived blockiness decreases from Figure 8(c) to Figure 8(a) the blockiness metric decreases from 0.37 to 0.001 for the original.


(a) (b)

(c)

Fig. 7. Frame nos: (a) 31 ($\mathcal{B}_F = 0.62$), (b) 40 ($\mathcal{B}_F = 0.38$), and (c) 55 ($\mathcal{B}_F = 0.28$), from the video stream coded at 88.5kbps.


(a) (b)

(c) (d)

Fig. 8. Frame no. 31 from the ”Mother-Daughter” sequence coded at different rates: (a) original ($\mathcal{B}_F = 0.001$), (b) 362.1 kbps ($\mathcal{B}_F = 0.17$), (c) 141 kbps ($\mathcal{B}_F = 0.37$), (d) 88.5 kbps ($\mathcal{B}_F = 0.62$).

5.2. NR packet loss metric

For our experiments we have used the elementary streams provided by Tektronix [19]. All clips were coded to the following specifications: Bit-rate=1.5 Mbps, Frame Rate=30 fps, Frame size = 352×240, and duration of 15 seconds. In our simulations, we have used the random packet loss generation software developed by NTT Mobile Communications Network, Inc (DoCoMo) for simulating packet loss in the MPEG-2 transport stream for various packet loss ratios (PLR). A snap shot of the affected video for PLR=1% and 5% for the “susi” sequence and the corresponding values of H_j are shown in Fig. 9. These figures show how H_j is proportional to the length of the artifacts along the macroblock edges. Fig. 11 shows the cumulative packet loss effect (F) for each frame of “susi”, and “table tennis” sequence for the no packet loss, PLR=1%, and PLR=5% scenarios. Note that, for both sequences the packet loss metric stays very close to zero for the original (as one should expect) and increase in proportion to the artifacts in each frame as described above.

6. CONCLUSION

In this paper, we have presented two novel NR metrics for 1) measuring block edge impairment artifacts in decoded video, and 2) evaluating the quality of reconstructed video in event of packet loss. Both NR metrics rely solely on the received video stream at the decoding end in a video streaming application, and relate well to the reconstructed video quality. In particular, both the proposed metrics monotonically increase with deteriorating video quality (increased compression and higher PLR, respectively) and are nearly zero for the original, lossless video stream. Because of their low computational complexity, the proposed metrics would be useful as part of a real-time monitoring tool for streaming video. Such metrics could also be a valuable part of an adaptive system for streaming video, e.g. as part of a feedback signal from a streaming media client to the streaming server to assist in the adaptive delivery of video resources to varying network conditions. Finally, they could also be used in other applications such as post processing of video frames for improved perceptual quality (e.g. error concealment, de-blocking filters).

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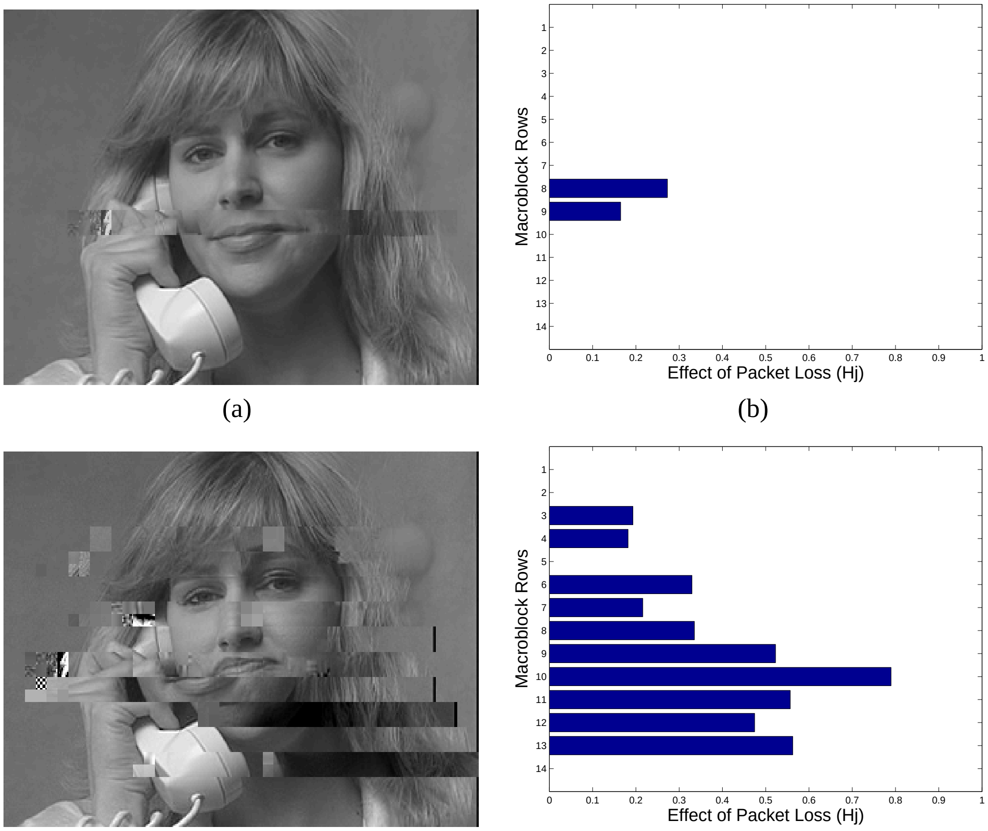

(a) (b)

(c) (d)

Fig. 9. A corrupted frame (frame no. 83) of susi sequence with (a) PLR=1%, (c) PLR=5% and (b,d) the corresponding measure H_j along the macroblock row edges

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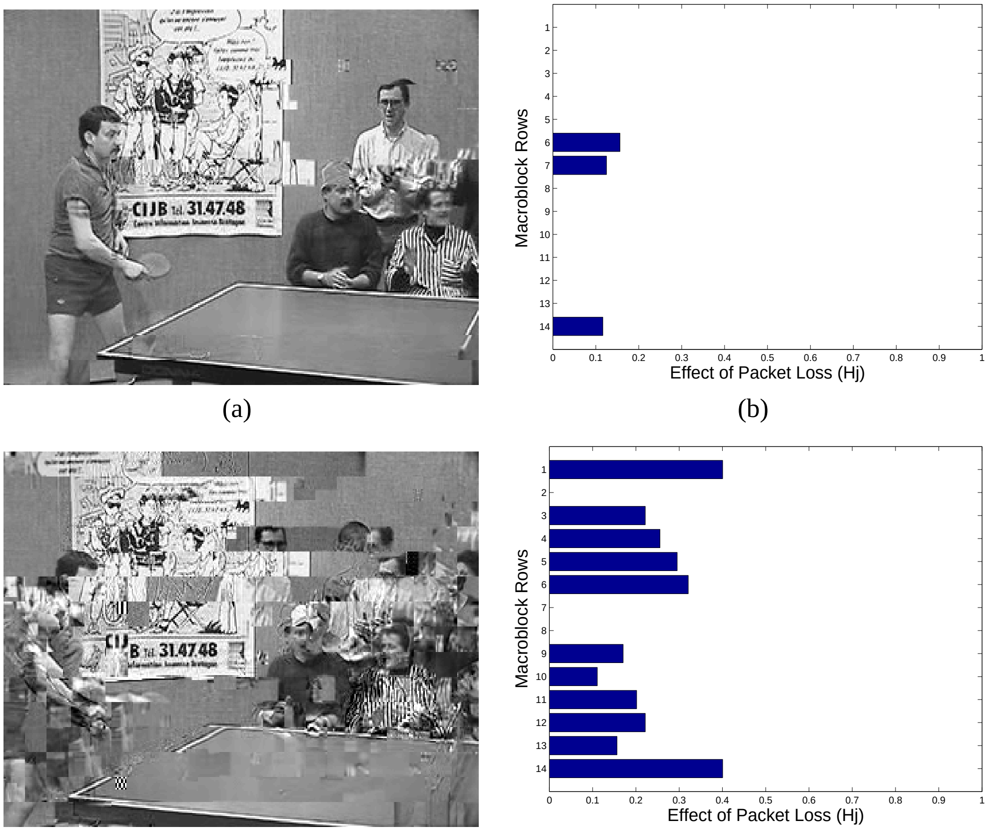

(a) (b)

(c) (d)

Fig. 10. A corrupted frame (frame no. 308) of table tennis sequence with (a) PLR=1%, (c) PLR=5% and (b,d) the corresponding measure H_j along the macroblock row edges

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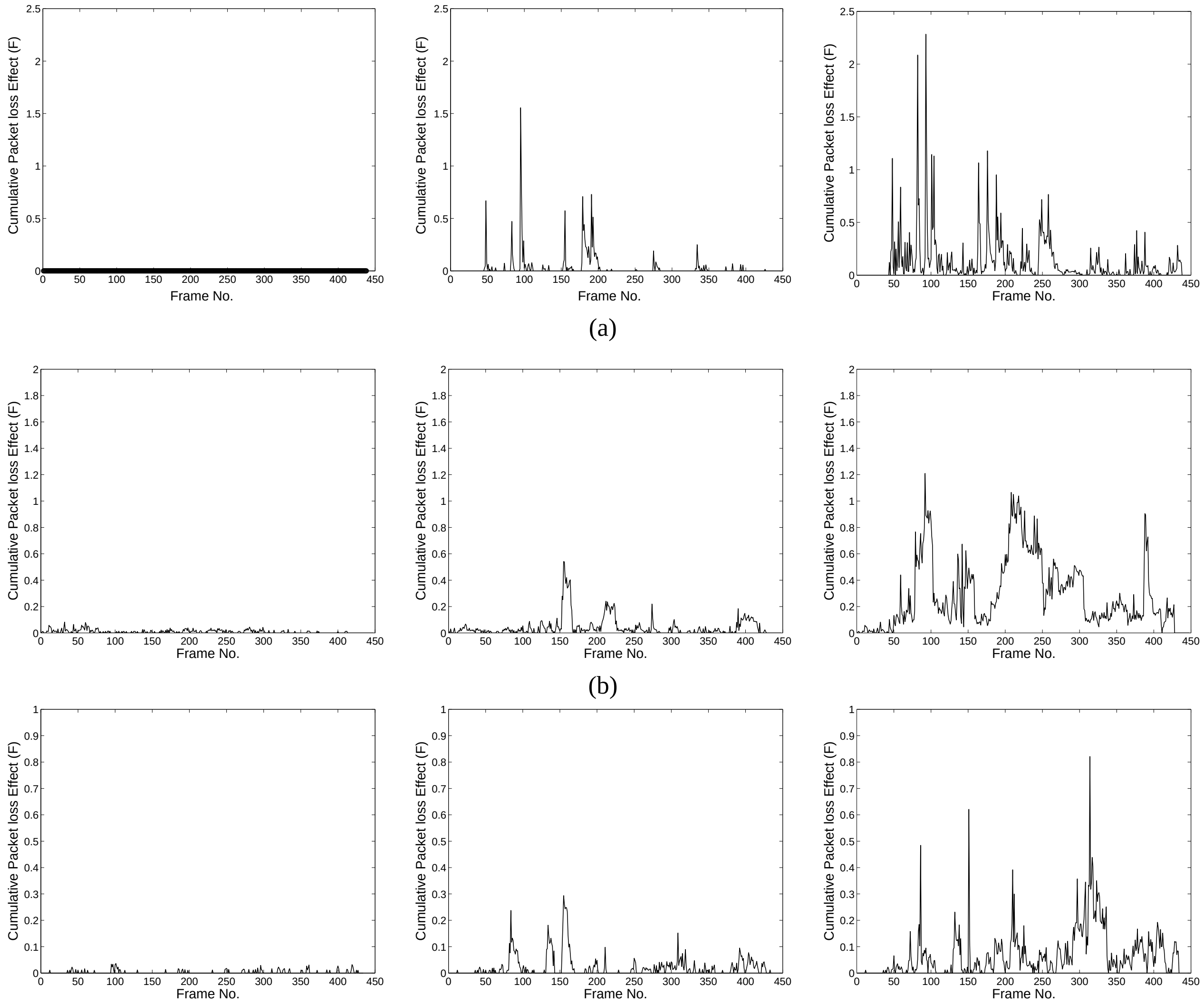

(a)

(b)

(c)

Fig. 11. The cumulative effect of packet loss (F) for original, PLR=1% and PLR=5% of (a) ‘susi’, (b) ‘mobile-calendar’ and (c) ‘flower garden’ sequences.