SPATIOTEMPORAL ADAPTIVE QUANTIZATION FOR THE PERCEPTUAL VIDEO CODING OF RGB 4:4:4 DATA

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ABSTRACT

Due to the spectral sensitivity phenomenon of the Human Visual System (HVS), the color channels of raw RGB 4:4:4 sequences contain significant psychovisual redundancies; these redundancies can be perceptually quantized. The default quantization systems in the HEVC standard are known as Uniform Reconstruction Quantization (URQ) and Rate Distortion Optimized Quantization (RDOQ); URQ and RDOQ are not perceptually optimized for the coding of RGB 4:4:4 video data. In this paper, we propose a novel spatiotemporal perceptual quantization technique named SPAQ. With application for RGB 4:4:4 video data, SPAQ exploits HVS spectral sensitivity-related color masking in addition to spatial masking and temporal masking; SPAQ operates at the Coding Block (CB) level and the Prediction Unit (PU) level. The proposed technique perceptually adjusts the Quantization Step Size (QStep) at the CB level if high variance spatial data in G, B and R CBs is detected and also if high motion vector magnitudes in PUs are detected. Compared with anchor 1 (HEVC HM 16.17 RExt), SPAQ considerably reduces bitrates with a maximum reduction of approximately 80%. The Mean Opinion Score (MOS) in the subjective evaluations, in addition to the SSIM scores, show that SPAQ successfully achieves perceptually lossless compression compared with anchors.

1. INTRODUCTION

Due to an increasing consumer demand for a high fidelity visual experience, the utilization of RGB 4:4:4 video data is becoming ubiquitous in various applications including digital cinema, computer vision, machine learning, medical telepathology, home entertainment and video conferencing. Therefore, to attain a high brightness, hue and saturation fidelity experience for the human observer, the direct coding of RGB 4:4:4 data is becoming more prevalent on, for example, High Definition and Ultra HD displays that are capable of the technical capabilities specified in ITU-R Recommendation BT.2020 [1] and BT.2100 [2]. This includes High Dynamic Range (HDR) tone mapping, Wide Color Gamut (WCG) and high bit-depth (deep color) RGB 4:4:4 playback. Support for the direct coding of RGB 4:4:4 data is included in the HEVC standard [3, 4] including JCT-VC standardized Range Extensions of HEVC HM (HM RExt) [5] and the Screen Content Coding Extensions of HM RExt (HM RExt + SCM) [6]. This includes the coding of RGB 4:4:4 data of up to 16-bits per sample (i.e., deep color RGB) [1, 2]. Due to the aforementioned HVS spectral sensitivity to photons that are perceived as green, the HEVC standard, by default, treats RGB data in the order of G, B and R. That is, the G channel is treated as the most important perceptual channel; this is similar to the way in which Y is treated as the most important perceptual channel in YCbCr data.

As regards the coding of RGB 4:4:4 video data in HEVC, the raw data is partitioned into Coding Units (CUs), which consist of three equal sized CBs (i.e., a Red CB, a Green CB and a Blue CB) within each CU [7]. Coding techniques, including spatiotemporal prediction [8], transform coding [9], quantization [4, 10, 11] and lossless entropy coding [12], operate in the same manner for both RGB 4:4:4 video data and YCbCr 4:4:4 video data. The main scalar quantization techniques in HEVC, known as URQ [4, 10] and RDOQ [11], are both always enabled by default; however, they are not perceptually optimized. URQ is designed to indiscriminately quantize transform coefficients in G, B and R (or Y, Cb and Cr) Transform Blocks (TBs) at equal levels according to the QStep; the QStep is controlled by a Quantization Parameter (QP) [4, 10]. RDOQ, which is utilized in combination with URQ, is a coefficient-level method designed to quantify quantization induced distortion and the number of bits required to encode a quantized coefficient. RDOQ chooses an optimal coefficient value, which is subsequently determined by ascertaining an appropriate trade-off between the bitrate and the distortion; this is known as the rate-distortion cost [11].

In the past decade, several video compression algorithms have been proposed for the direct coding of RGB 4:4:4 data. These techniques include those proposed by Song et al. [13], Kim et al. [14], Zhao and Ai [15], Huang et al. [16], Huang and Lei [17] and Shang et al. [18]. The methods proposed in [13]-[17] are designed primarily to reduce statistical redundancies only. In other words, psychovisual redundancies in raw RGB 4:4:4 data are not taken into account; therefore, perceptual optimization is neglected thus potentially leading to a waste of bits during the residual coding process. The most recent relevant technique proposed (Shang et al. [18] in 2019) is a coefficient-level perceptual quantization method for HEVC; this method employs Quantization Matrices (QMs). The main drawbacks of this method are as follows: firstly, it is not perceptually adaptive (i.e., the QMs are static and do not adapt to the raw data); secondly, it focuses on spatial masking only.

To reiterate, in this paper we propose a novel spatiotemporal perceptually adaptive quantization method, named SPAQ. SPAQ exploits HVS psychovisual redundancies inherent in raw RGB 4:4:4 video data. More specifically we employ color masking by accounting for spectral sensitivity of the HVS (i.e., quantizing data in the B and R channels more coarsely), spatial masking in high variance regions of the raw data and PU-level temporal masking in high motion regions of the raw data. Our technique adaptively discards perceptual redundancies in each color channel from the raw RGB 4:4:4 data by virtue of CB-level perceptual quantization. Compared with the aforementioned previously proposed methods, our technique provides some key advantages, which are as follows: 1) SPAQ employs color masking, spatial masking and temporal masking, and 2) SPAQ is adaptive; therefore, every sequence is perceptually compressed according to the unique characteristics of the sequence being processed.
components are predicted from the G component; this method
utilizes an adaptive inter-plane weighted prediction method; this
method achieves coding efficiency gains of up to 20%. Kim et al. [14]
propose an inter-color compensation scheme for RGB 4:4:4 video
coding. It facilitates the interpretation of photon waves in the
following wavelength ranges: 650nm (long), 510nm (medium) and 475nm
(short). As such, these long, medium and short photon waves are
interpreted as red, green and blue, respectively [21]-[23]. In terms of
spectral sensitivity and brightness perception, the HVS is very
sensitive to medium photon waves, which are perceived as green
(see Fig. 1). The RGB color model subsequently gave rise to the
RGB color space for utilization on computing and visual display
technologies. The interaction of the HVS with the combination of
physical luminance and photon waves in nature, emitted from a
display unit — which constitutes the light source — is the physical
process by which visible light (photons) and the associated
luminance are visually perceived as a combination of brightness,
hue and saturation. On computing devices, RGB color values are
typically represented as integer triplets; i.e., $2^{N−1}$, where $h$
denotes the bit-depth of the RGB data (bits per sample per channel). In
the case of 10-bits per sample raw RGB 4:4:4 video data (i.e., 30-bit
deep color), $R \in [0,1023]$, $G \in [0,1023]$ and $B \in [0,1023]$.

In terms of the relevant state-of-the-art algorithms that are
present in the literature, Song et al. [13] propose a block adaptive
inter-color compensation scheme for RGB 4:4:4 video coding. It
reduces inter-color redundancy in RGB channels by employing a
novel linear model; this method achieves coding efficiency gains by
approximately 20%. Kim et al. [14] propose an inter-color
redundancy technique for RGB 4:4:4 video coding in which they
utilize an adaptive inter-plane weighted prediction method; this
method attains coding efficiency gains of up to 21%. Zhao and Ai
[15] propose a color redundancy reduction technique for RGB
4:4:4 intra coding. In this technique, the authors employ an
adaptive inter-color prediction scheme whereby the B and R
components are predicted from the G component; this method
improves coding efficiency by around 30%.

Huang et al. [16] propose an adaptive weighted distortion
scheme for utilization in the Rate-Distortion Optimization (RDO)
process within HEVC. In this method, PSNR is quantified by
taking the importance of the G channel — relative to the B and R
channels — into account; this technique improves coding
efficiency by up to 44%. Huang and Lei [17] propose a cross
component technique designed for the inter-prediction process in
HEVC. In this method, statistical correlations within the R, G and
B color components are identified in the motion compensation
prediction signal, from which a residual prediction parameter is
derived; this technique achieves coding efficiency gains of up to
31%. Shang et al. [18] propose a perceptual quantization technique
for HEVC. In this method, the authors develop frequency
weighting matrices based on a Contrast Sensitivity Function (CSF)
model, from which QMs are derived. This method is a spatial
masking technique that operates at the transform coefficient level,
it achieves coding efficiency gains of up to 21%.

The principle drawback of the previously proposed RGB
4:4:4 video coding techniques proposed in [13]-[17] is that they
are not perceptually optimized. Though they achieve noteworthy
coding efficiency improvements, the bitrate reductions could have
been much greater had they taken into account the spatiotemporal
perceptual redundancies inherent in the raw RGB 4:4:4 data. The
QM technique proposed in [18] accounts for HVS perceptual
redundancies; however, it does have certain shortcomings. The
authors of this method adopt a spatial CSF model that is not
designed for RGB 4:4:4 data. Furthermore, this QM technique
comprises static, non-adaptive intra and inter QMs for spatial
masking only. This method does not account for the characteristics
of different RGB 4:4:4 video sequences, nor does it take temporal
information into account.

3. PROPOSED SPAQ TECHNIQUE

SPAQ is a spatiotemporal perceptual quantization technique in
which HVS spectral sensitivity, spatial variance and motion vector
information are exploited. SPAQ is based on similar principles to
our previously proposed methods known as C-BAQ [24] and
FCPQ [25]. Both C-BAQ and FCPQ are spatial-only perceptual
quantization techniques designed to improve upon AdaptiveQP
[26]. AdaptiveQP is a perceptual quantization method that works
in combination with URQ and RDOQ in HEVC to further reduce
bitrates. It is designed to compute the spatial variance of $Y$ (or $G$
CB sub-blocks only. Consequently, AdaptiveQP adjusts the QP of
an entire $2N$×$2N$ CU without taking into account the variance of
data in the sub-blocks of chroma $Cb$ (or $B$) and $Cr$ (or $R$) CBs,
which is a significant shortcoming of the technique. With
application for the perceptual coding of YCbCr data, C-BAQ [24]
improves upon AdaptiveQP by taking into account the combined
spatial variance of data in the sub-blocks of $Y$, $Cb$ and $Cr$ CBs; the
CU-level QP is thus adjusted accordingly. FCPQ [25] expands
upon C-BAQ by computing QPs at the CB level. That is, FCPQ
separately adjusts the QPs for the $Y$ CB, the $Cb$ CB and the $Cr$
CB based on the variances of data in the sub-blocks of all three CBs.
Consequently, three CB-level QPs are signaled in the Picture
Parameter Set (PPS) [27, 28]; this is also the case for SPAQ.
SPAQ significantly improves upon AdaptiveQP, C-BAQ and
FCPQ in the following areas: SPAQ accounts for color masking,
spatial masking and temporal masking. Furthermore, AdaptiveQP,
C-BAQ and FCPQ are designed to perceptually decrease the QP
for smooth (low variance) regions of raw data regardless of the
QStep employed during the coding process, which unnecessarily
increases bitrates. Because SPAQ employs color masking and
temporal masking, it is not necessary to decrease the CB-level QP
in smooth regions of an RGB 4:4:4 sequence.

Fig. 1: The relative spectral sensitivity of the HVS to photons of various
wavelengths (data: National Physical Laboratory [19]). Note how, in terms of
the perceived brightness, saturation and hue of color, the HVS is
significantly more sensitive to the photon energies that the HVS interprets
as the color green.

The rest of this paper is organized as follows. Section 2
includes a detailed overview of the relevant literature. Section 3
provides detailed background information on the SPAQ algorithm.
Section 4 includes the evaluation, results and discussion of the
proposed method. Finally, section 5 concludes the paper.
In terms of the SPAQ algorithm, the CB-level perceptual QPs, denoted as $Q_G$, $Q_B$, $Q_R$, are shown in (1)-(3), respectively:

$$Q_G = t_G + \left( q_G + \left[ 6 \times \log_2(G) \right] \right) \in \left[ o, o_{\max} \right]$$

(1)

$$Q_B = t_{B,R} + \left( q_B + \left[ 6 \times \log_2(B) \right] \right) \in \left[ o, o_{\max} \right]$$

(2)

$$Q_R = t_{B,R} + \left( q_R + \left[ 6 \times \log_2(R) \right] \right) \in \left[ o, o_{\max} \right]$$

(3)

where $t_G$ and $t_{B,R}$ correspond to perceptual QP offsets related to temporal masking (via motion vector magnitude data in PUs) in RGB 4:4:4 video data, respectively, where $q_G$, $q_B$ and $q_R$, denote the frame-level QPs for the G, B and R channels, respectively and where $G$, $B$ and $R$ refer to variables comprising the spatial variance information in each G, B and R CB sub-block, respectively. These spatial masking-related and temporal masking-related perceptual QP offsets are employed to perceptually adjust, at the CB-level, the frame-level QP for each color channel. Variable $o$ refers to the mean CB-level perceptual QP offset in HEVC HM RExt, $o_{\max}$ is the maximum allowable CB-level QP offset in HEVC HM RExt ($o_{\max} = 12$ [29]), $w$ refers to the maximum number of CB-level QP offsets permitted in HEVC HM RExt ($w = 12$ [29]) and where $p_k$ refers to the $k^{th}$ CB-level QP offset. The perceptual QP offset range is lower for G data, as compared with B and R data, because humans are more sensitive to compression artifacts in G data due to the HVS spectral sensitivity phenomenon (see Fig. 1). Variables $t_G$ and $t_{B,R}$ are computed in (5)-(8), respectively. $G$, $B$ and $R$, and the associated variables, are quantified in (9)-(11), respectively:

$$t_G = \frac{o}{2} \quad \text{if } M(n,i) > V,$$

(5)

$$t_{B,R} = \frac{o}{2} \quad \text{if } M(n,i) > V,$$

(6)

$$V = \frac{1}{p} \sum_{i=1}^{p} M(n,i)$$

(7)

$$M(n,i) = \sqrt{M^2_v + M^2_z}$$

(8)

where $M(n,i)$ corresponds to the magnitude of motion vector $MV$ in a PU and where $V$ is the arithmetic mean motion vector magnitude in a PU within an entire frame. More specifically, $M(n,i)$ denotes the magnitude of a motion vector in a PU within the $i^{th}$ CU of the $n^{th}$ frame and where $P$ corresponds to the total number of PUs in the $n^{th}$ frame. Subscripts $x$ and $y$ correspond to the coordinates $(x,y)$ of motion vector $MV$. $M(n,i)$ constitutes an adaptive threshold value related to temporal masking, whereby magnitude $M(n,i)$ of motion vector $MV$ must exceed $V$ in order for a region to be considered as high motion. Note that, because the G, B and R CBs are of equal size (see Fig. 3), the motion vectors in each G, B and R Prediction Block (PB) do not differ in magnitude (i.e., no scaling is required), which is the reason why SPAQ operates at the PU level in relation to measuring motion vector magnitudes. In terms of perceptual quantization adjustments as a result of temporal masking, recall that the HVS is much less sensitive to compression artifacts in high motion regions of video data [30]. We now define $G$, and the associated variables, in (9)-(11), respectively:

$$G = \frac{s \cdot g + m_G}{g + s \cdot m_G}$$

(9)

$$g = 1 + \min \left( \sigma^2_{o,d} \right), \quad \text{where } d = 1, \ldots, 4$$

(10)

$$m_G = \frac{1}{c_G} \sum_{j=1}^{c_G} g_j$$

(11)

where variable $s$ refers to a scaling factor for normalizing the spatial activity of a G CB ($s = 2$ by default in HEVC [29]), where $g$ corresponds to the non-normalized variance of a G CB, where $m_G$ denotes the mean variance of all $2N \times 2N$ G CBs belonging to the current picture of a frame, where $\sigma^2_{o,d}$ refers to the variance of samples in an $N \times N$ CB sub-block $d$ within a G CB and where $C_G$ denotes the number of $2N \times 2N$ G CBs in the current picture. Note that the equations for quantifying the variances of $B$ and $R$, from Eqs. (2) and (3), respectively, are essentially identical to those shown in Eqs. (9)-(11), which calculate $G$ from Eq. (1). Only the symbols that express the numerical data for $B$ and $R$ differ.
In a side test, further subjective evaluations were undertaken in [31, 32]. In order to ascertain the perceptual compression efficacy of SPAQ versus anchors, the subjective evaluations — as quantified by G, B and R PSNR (dB) percentage values — is considerably inferior for SPAQ. This is due to the higher levels of quantization applied to B and R data, in particular, in accordance with color masking, spatial masking and temporal masking based on a HVS model. However, these substantial PSNR dB reductions have little correlation with subjective MOS and SSIM scores, other than when the initial QP is very high (e.g., in the QP = 37 tests). In the evaluations for SPAQ versus anchors, we have proved that high levels of perceptual quantization can be applied to G, B and R components without incurring visually conspicuous compression artifacts; to reiterate, this proved to be the case in the QP 22 and QP 27 tests. Moreover, the evidence provided in these experiments reaffirms the fact that the PSNR metric has a poor correlation with human visual perception.

5. CONCLUSION

In this paper, we propose a spatiotemporal perceptual quantization technique, named SPAQ, for application with RGB 4:4:4 video data. We exploit HVS spectral sensitivity, color masking, spatial masking and temporal masking to discard perceptually irrelevant samples from each sequence. Compared with anchors, SPAQ achieves vast bitrate reductions, of up to 81%, while achieving perceptually lossless compression (in the QP 22 and QP 27 tests). In a side test, further subjective evaluations were undertaken versus the raw RGB 4:4:4 sequences; MOS = 5 was chosen by the participants for SPAQ on all sequences (QP = 22 test only). SPAQ thus achieves perceptually lossless coding, versus the raw data, at QP = 22. Finally, SPAQ attains moderate encoding time and decoding time improvements compared with anchors.
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