Journal of King Saud University – Computer and Information Sciences 32 (2020) 784–793

Contents lists available at ScienceDirect

Journal of King Saud University – Computer and Information Sciences

journal homepage: www.sciencedirect.com

High efficient video coding using weighted entropy with optimized quantization matrix

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ARTICLE INFO

Article history:
Received 18 August 2017
Revised 6 November 2017
Accepted 20 November 2017
Available online 7 December 2017

Keywords:
High-Efficiency Video Coding (HEVC)
Video compression
Quantization matrix(QM)
PSNR
Optimized quantization matrix

ABSTRACT

As the concept of quantization matrix becomes an important feature in recent video CODECs, an optimized quantization matrix is being considered in the High-Efficiency Video Coding (HEVC) standard. This paper describes the entropy encoding by familiarizing optimized quantization matrix, and so higher rate of compression can be accomplished over the improved entropy encoding. Experiments show that for the eight benchmark video sequences and PSNR for varying rate of data transmission is explored. Comparative analysis is made with the improved (WE-Encoding) and standard entropy encoding based on the performance measurements. The simulation results show that the proposed method (WE-OQM) can save the originality of the decoded video sequence far better even though the compression rate is increased. In addition, the overall analysis states that the proposed method is 35.29% better than the Standard Encoding and 62.5% better than the WE-Encoding.

1. Introduction

Due to the rapid development of multimedia and internet usages, efficient transmission of video through the network is a primary concern. To transmit video stream efficiently through internet video coding procedure is used which compresses digitized video data. The essential pre-requisite of video coding is to transmit less video information without compromise on quality. Practical applications of video coding include high definition television, video streaming, video communication, etc. (Yeh et al., 2015). Visual Coding Experts Group (VCEG) enacted early video coding standards such as MPEG-1, MPEG-2 and H.264/AVC (Correa et al., 2012). Later, the Joint Collaborative Team on video coding (JCT-VC) passed the High-Efficiency Video Coding (HEVC) standard (Han et al., 2012; Sullivan et al., 2012, 2013). The latest HEVC standard is the advanced form of H.264/MPEG4 part 10-Advanced Video Coding (AVC) standard (Sandeep et al., 2015). The advanced HEVC have been proposed to assist high bit rates, spatial and reliable scalability, multi-view video coding and additional colour formats (Xiang et al., 2011). Therefore the key objective of HEVC is to improve the multimedia performance with low complexity and computational cost (Choi and Choi, 2013).

HEVC involves multiple coding tools namely Prediction unit, coding unit, transform unit in quadtree coding block partitioning tool. The picture is subdivided into many blocks for prediction and coding in quadtree tool (Bossen et al., 2012). While comparing with conventional video coding standards such as MPEG and H.264/AVC, the HEVC performance is great in terms of bit rates, but the encoding section of HEVC suffers from drawbacks such as computational complexity and storage problems (Correa et al., 2012; Sunil Kumar et al., 2016a,b; Shanableh et al., 2013). Intra coding offers fine quality videos, but it has certain drawbacks. On the other hand, quantization can improve the subjective quality of videos by obtaining higher peak signal to noise ratio (PSNR) (Wang et al., 2015). By adjusting the quantization parameter, bit-rate control can be performed efficiently. Using bit-rate control the target bits are precisely allocated (Sun et al., 2014). Several quantization methods are given in the following literature reviews (Zhou et al. 2015).

In early video codecs, DCT coefficients were primarily quantized according to a uniform scalar quantizer (USQ) (Sun et al., 2013;

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https://doi.org/10.1016/j.jksuci.2017.11.004
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Winken et al., 2015). Later on, in addition with USQ dead zone [USQ + deadzone (DZ)] was adopted in MPEG-4, AVS, and early H.264/AVC reference codes (Yin et al., 2015; Sunil Kumar et al., 2016b). For an advanced version of H.264/AVC as well as HEVC, rate distortion optimized quantization (RDOQ), as well as Block Level Adaptive Quantization method (BLAQ), has been proposed (Wang et al., 2015). A popular Soft decision quantization (SDQ) technique is implemented for video coding to achieve coefficient-level rate-distortion optimized quantization (RDOQ) in (Yin et al., 2015).

The remainder of this paper is organized as follows. First, related works on various entropy encoding techniques in the literature are reviewed in Section 2. A brief description of the techniques used for entropy encoding in the HEVC video coding standard in its current state of development is presented in Section 3. Section 4 describes the methodology used in this paper for optimizing quantization matrix in HEVC. Section 5 presents experimental results for a set of eight video sequences, analyzing the tradeoff between encoding performance and computational cost. Finally, conclusions are presented in Section 6.

2. Review on contributions in HEVC

2.1. Encoding concepts in HEVC

Other related works in HEVC include a novel algorithm namely Adaptive Fast Quadtree Level Decision (AFQLD) algorithm to make faster decision on Coding unit splitting in HEVC, which is introduced by Honrubia et al. (2016) in 2015. Also, the fast decision-making problem is addressed by Hu and Yang (2015) in 2016 and is overcome with the use of fast intra mode decision (OIMD) algorithm. In the same year, Yeh et al. (2015) propose intra prediction model for increasing the performance of intra coding in HEVC. Moreover, by enhancing the video quality, intra frame rate is controlled with the help of gradient-based R-lambda (GRL) method experimentally studied by Wang et al. (2014). In contrast, several methods are focussed on transform coding in HEVC. In 2013, Nguyen et al. (2013) had introduced the quadtree-based partitioning dubbed as residual quadtree that supports in increasing the size of transform blocks and in 2012 Sole et al. (2012) have worked on transform coefficient coding which includes the scanning patterns and coding methods.

2.2. Customization of QM

In early video codecs, the Quantization Matrix (QM) was predominantly developed to focus on the visual quality improvement. In 2010, Malavika Bhaskaranand introduced Campbell's spectral entropy and coefficient rate. Since spectral entropy method has entailed delay, this scheme could be used to customize QM on a per-frame basis in contrast to macroblock adaptive QM schemes proposed for H.264 video encoders. Also the QM design method involves delay but is not computationally intensive (Bhaskaranand and Gibson, 2010). With the rapid development of video services Visual Display Unit (VDU), is newly used for displaying video data in High Definition (HD) and Ultra HD (UHD) display resolutions. Recently, some successful approaches have been presented for resolution. Thus to further improve the display resolution, Lee Prangnell recently proposed a Human Visual System and a 2D Contrast Sensitivity Function Quantization Matrix method. Based on the display resolution of the target VDU, it has taken the consideration to determine the appropriate levels of quantization required to reduce unwanted video compression (Li and Yang, 2016).

2.3. Problem statement

As per the above review, very few researchers have worked on customizing QM as per their requirement. They have made the QM adaptive to handle the environmental constraints. Despite the fact that the QM customization has been reported as promising in the literature, they are information specific processes. Since the QM is made adaptive, it requires sufficient information process to generate its own QM. As a result, the QM might be generated based on the contents and the characteristics of the subjected video sequence (Bhaskaranand and Gibson, 2010). It obviously increases the processing time, which is sensitive in real-world applications. Secondly, the sensitivity to quantization levels in (Li and Yang, 2016) put a bottleneck for the generalized operation of the HEVC. The most important concern is that the reported QM customization can support H.264 encoding, but uncertain to HEVC. The literature lags in optimizing the QM and so to improve the encoding performance of HEVC.

2.4. Contributions

This paper contributes to improve the HEVC standard in two stages. They are given below.

- In the first stage, the optimized method concept in the CABAC scheme is adopted. As a result, the encoding efficiency can be improved.
- In the second stage, the QM is optimized to perform the quantization operation. To facilitate the optimization, a maximization model is formulated. The model is solved using an iterative meta-heuristic update, and so the optimized QM is obtained.
- Simulation study is carried out with prevailing QM on encoding benchmark video sequences of different contents

3. WE-OQM based HEVC

3.1. Proposed architecture

The proposed HEVC architecture exploits WE-Encoding principle (Sunil Kumar et al., 2017) in the CABAC encoder. Further, optimization of QM is performed in this paper and included in the quantization process of the HEVC architecture. It is to be observed that the literature reports adaptive QM, which is different from optimizing QM. Adaptive QM gets its values based on the contents of the video sequences, whereas the optimized QM maintains its performance for diverse video sequences. The association of the WE-encoding principle and optimized QM with the HEVC standard is portrayed in Fig. 1, where the red coloured block shows suggested changes in the HEVC architecture. The details of WE-Encoding (Sunil Kumar et al., 2017) are discussed further, whereas the detailed information about the HEVC operation is given in (Sullivan et al., 2012). The proposed QM optimization process is discussed in the next sub-section.

3.2. Weighted entropy encoding for HEVC

Assume X be the set of M video sequences $\{x_1, x_2, \ldots, x_M\}$, with an individual x_k for $1 \leqslant k \leqslant M$ and their unconditional attribute vector of $[y_1, y_2, \ldots, y_N]^T$, where N denoted the number of attributes and y_j had a province value which can be valued by $[y_{1,j}, y_{2,j}, \ldots, y_{ni,j}]$ for $1 \leqslant j \leqslant N$, where y_j symbolizes the number of dissimilar values in the attributey_j . Assume that the attribute y_j be the random variable, the random vectors $[y_1, y_2, \ldots, y_N]^T$ are designated as Y . The attribute x_i is denoted as $[x_{i,1}, x_{i,2}, \ldots, x_{i,m}]^T$.

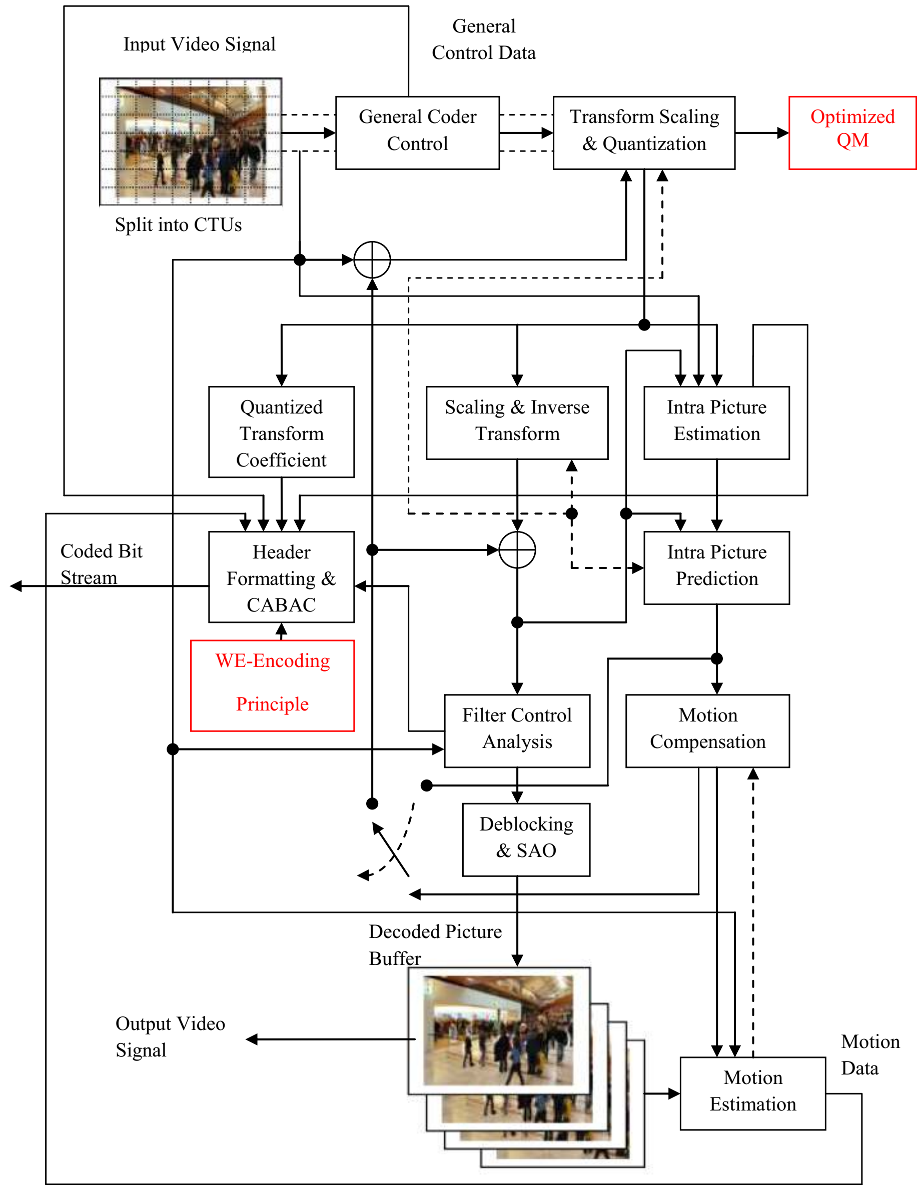

Fig. 1. Standard architecture of HEVC.

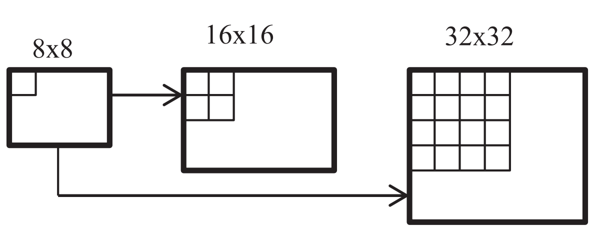

Fig. 2. To create a 16×16 QM, each entry in an 8×8 QM is upsampled and replicated into a 2×2 region, while each entry in an 8×8 QM is upsampled and replicated into a 4×4 region to create a 32×32 QM.

For each attribute, the entropy is weighted with the aid of reverse sigmoid function,

$$W_i = 1 - \text{logit}^{-1}(w_i E_i) \tag{1}$$

$$W_i = 1 - \frac{1}{1 + e^{-w_i E_i}} \tag{2}$$

The weighted entropy model claims in determining optimal w_i based on the pixel-wise relationship of the decoded video sequence with the original video sequence. Hence, the optimal w_i can be expressed as a maximization problem given below.

$$w^* = \arg\max_{w_i} \sum_{l=1}^{M_s} \left(2\log x_l^{\max} - \left[\log \frac{1}{|x_l|} \sum_u \sum_v \left(x_l(u,v) - \widehat{x}_l(u,v) \right)^2 \right] \right) \tag{3}$$

where $x_l(u,v)$ and $\widehat{x}_l(u,v)$ brings up to $(u,v)^{th}$pixel element of a frame corresponds to l^{th} video sequence and the decoded video sequence, respectively. Finally, to optimize the entropy weight, a novel firefly algorithm (Bhatnagar and Gupta, 2016; Rao Yarrapragada and Bala Krishna, 2017) is exploited. This algorithm helps to solve the objective function given in Eq. (3).

Firefly algorithm: Xin-She Yang proposed metaheuristic firefly algorithm, which is inspired by the flashing behaviour of fireflies. Generally, the fireflies create luminescent flashes as a signal system in order to communicate with other fireflies, particularly to prey attractions. In addition, the flashing light is created by a procedure termed as Bioluminescence.

The assumptions made in the firefly algorithm are represented as follows:

(a) All fireflies will be attracted to every other firefly in spite of their sex, specifically to say that they are unisex.
(b) The attractiveness and brightness minimum as the distance maximum and are also proportional to each other. In addition, the fewer bright will be moving towards the brighter one. If there is no brighter one it will move randomly.
(c) By the shape of the objective function, the brightness of a firefly is determined or affected.

4. Optimized quantization matrix for HEVC

4.1. Static quantization matrices (QMs)

The Static Quantization matrices contribution is taken from the literature. Due to the advantage of frequency dependent scaling, the HVS-CSF QM technique presented in (Wang et al., 2001) has taken as the default intra QM in HEVC. The HVS-CSF constructed 8×8 intra QM, and the 8×8 inter QM that is derived from the intra QM, have been exposed to be the actual QM solutions in HEVC. The default QMs in HEVC permit low frequency AC to transform coefficients to be quantized with a finer quantization step size in 8×8 TBs (Sze et al., 2014). Even though the HEVC standard supports up to 32×32 TBs, default 16×16 and 32×32 QMs were not offered in HEVC design. Instead of that, they are attained from upsampling and replication of the 8×8 QMs. More precisely, for creating a 16×16 QM, each entry in an 8×8 QM is upsampled and replicated into a 2×2 region. Also each entry in the same 8×8 QM is upsampled and replicated into a 4×4 region to create a 32×32 QM (Sze et al., 2014). This QM replication process guarantees that transform coefficients, in 16×16 and 32×32 TBs, are nearly quantized in accordance with their frequency content (see Fig. 3); distinguished that 8×8 QM upsampling and replication process for the AQM technique. Because HEVC has worked up to a total of 20 QMs, this 8×8 QM upsampling and replication process has been intended to minimize computational complexity with respect to the memory requirements desired to store the QMs (Sze et al., 2014).

As stated, the default 8×8 intra QM in HEVC is derived from a HVS-CSF based approach (Wang et al., 2001; Rodríguez-Vallejo et al., 2016). In the conventional technique, the HVS has demonstrated as a nonlinear point transformation charted by the Modulation Transfer Function (MTF) (Mannos and Sakrison, 1974). A CSF-based MTF was well defined as follows:

$$W(f) = e(g + qf)\exp(-q(f)^r) \tag{4}$$

where f is the radial frequency in cycles per degree of the visual angle, also e, g,q, and r were constants.According to Daly's 2D HVS-CSF approach in (Rodríguez-Vallejo et al., 2016), the MTF is estimated using modified constant values $e = 2.2$, $g = 0.192$, $q = 0.114$ and $r = 1.1$ (Tech et al., 2016). The MTF is used to produce a 2D FWM, $W(k,l)$, consisting of floating point values from which the threshold values of QM integer were derived. $W(k,l)$ is calculated in (5):

$$W(k,l) = \begin{cases} 2.2(0.192 + 0.114f'(k,l))\exp(-(0.114f'(k,l))^{1.1}) & f'(k,l) > f_{\max} \\ 1.0 & otherwise, \end{cases} \tag{5}$$

where the variables k and l in $W(k,l)$ symbolizes the horizontal and vertical floating point values, $f'(k,l)$ is the normalized radial spatial frequency in cycles per degree and fmax represents the frequency of 8 cycles per degree (i.e., the exponential peak).On account of interpreting the fluctuations in the MTF as a function of viewing angle θ, the normalized radial spatial frequency, $f'(k,l)$, has demarcated by angular dependent function$A(\theta(k,l))$. Both $f'(k,l)$ and $A(\theta(k,l))$ were measured in (6)–(9).

$$f'(k,l) = \frac{f(k,l)}{A(\theta(k,l))} \tag{6}$$

$$f(k,l) = \frac{3.14}{180\sin^{-1}(1/\sqrt{1+d^2}))} \times \sqrt{f(k)^2 + f(l)^2} \tag{7}$$

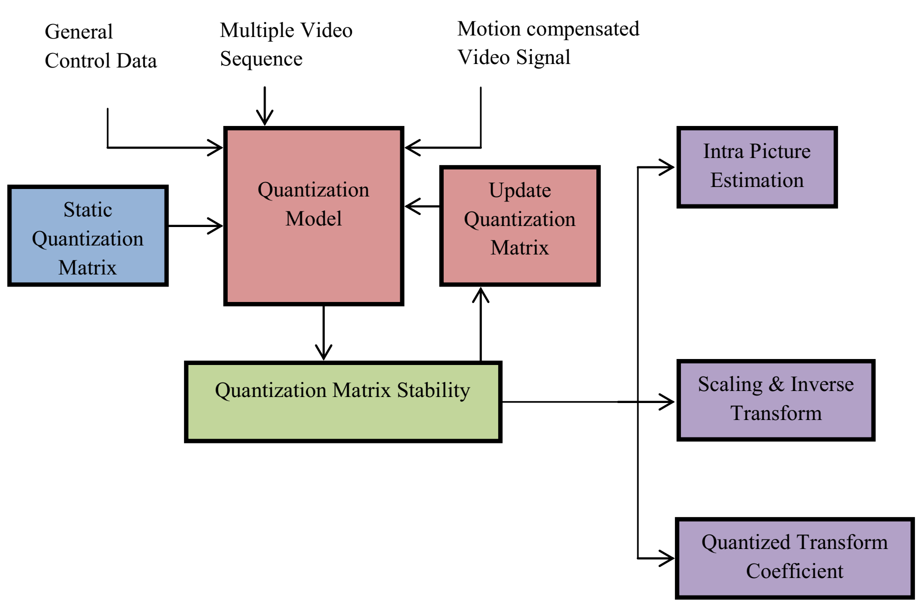

Fig. 3. Weighted Entropy Encoding with Optimized QMs.

$$A(\theta(k,l)) = \frac{1-p}{2}\cos(4\theta(k,l)) + \frac{1+p}{2} \tag{8}$$

$$\theta(k,l) = \arctan\left(\frac{f(k)}{f(l)}\right) \tag{9}$$

where d signifies the perceptual distance of 512 mm and p represents the symmetry parameter with the value 0.7 (Mannos and Sakrison, 1974). Since symmetry parameter and angular dependent function are directly proportional, $A(\theta(k,l))$ decreases at approximately 45° as such p decreases; this in turn decreases $W(k,l)$ and increases $f'(k,l)$. The distinct vertical and horizontal frequencies are calculated in (10):

$$f(l) = \frac{l-1}{\Delta \times 2M} \quad for \quad l = 1,2,....,M; \tag{10}$$

$$f(k) = \frac{k-1}{\Delta \times 2M}, \quad for \quad k = 1,2,....,M; \tag{11}$$

where Δ indicates the dot pitch value of 0.25 mm and M denotes the number of vertical and horizontal radial spatial frequencies.

4.2. Optimization of QMs

In order to optimize the quantization matrix, the static quantization matrix has taken as default from where the quantization model process takes place. In quantization model the Multiple Video Sequence, General Control Data from general coder control block and motion compensated video signals obtained from the spatial relevance of video frames are given as input which is then quantized in the form of multiple evaluation scores, and this can be updated iteratively to attain the desired evaluation score. Furthermore, the resultant values are fed back to the blocks such as Quantized Transform Coefficient, Scaling & Inverse Transform, and Intra Picture Estimation Blocks present in HEVC architecture.

On account of determining the PSNR, mean square error of the quantized multiple video sequence is calculated in (11):

$$MSE = \sum_{h=1}^{N_v} \frac{1}{N_r \cdot N_f \cdot N_c} \sum_{a=0}^{N_r-1} \cdot \sum_{b=0}^{N_f-1} \cdot \sum_{c=0}^{N_c-1} [V_I^{(h)}(a,b,c) - V_{R[Q]}^{(h)}(a,b,c)]^2 \tag{12}$$

where $V_I^{(h)}(a,b,c)$ and $V_{R[Q]}^{(h)}(a,b,c)$ indicates the pixel value of original and quantization matrix of decoded video signals in position (a,b) from the c^{th} frame of h video sequences respectively, N_r, N_f denotes the number of pixel position, N_c represents the number of frames in multiple video sequence.

Therefore the PSNR of quantized multiple video sequence is given as:

$$PSNR = 10\log_{10} \sum_{h=1}^{N_v} \frac{\max{[V_I^{(h)}]}^2}{MSE} \tag{13}$$

where N_v represents the number of a video sequence, $V_I^{(h)}$ indicates original video signal of h video sequence.

For determining the optimal solution constructed with the pixel-wise relationship of the decoded video sequence with the original video sequence, the proposed quantization model is presented. Hence, the method of determining optimal solution can be expressed as maximization problem given as follows:

$$[Q^*] = \arg\max_{[Q]} \frac{1}{N_v} \sum_{h=1}^{N_v} \left[10\log_{10} \frac{\max{[V_I^{(h)}]}^2}{MSE}\right] \tag{14}$$

$$Q_m^+ = Q_m + r_1[Q_m - Q_{best}] \tag{15}$$

where $[Q^*]$ is the optimized quantization matrix and $[Q]$ represents quantization matrix in Eq. (13). In Eq. (14), Q_m^+, Q_m and Q_{best} refer to the updated quantization matrix, old quantization matrix and best of the quantization matrices achieved till the current iteration, respectively. r_1 is an arbitrary integer generated within the interval $[-1,1]$. In Fig. 4, the flowchart of optimized QMs is illustrated. Here, the static quantization matrix is given as input to the population of quantization matrix. Subsequently, the evaluation of Quantization matrix is exploited by Mean Square Error (MSE). On the basis of evaluation, the selection of optimal quantization matrix procedure takes place, and then the quantization matrix is updated. If the terminate criteria is reached, the process will return the optimized quantized matrix otherwise, the process will repeat.

Algorithm: Pseudo code to solve the optimized quantization matrix

1 Inputs: Random quantization matrix, General control data, Multiple video sequence, Motion compensated video signals
2 Outputs: Quantized transform coefficients, Scaling & inverse transform, Intra picture estimation
3 Initialize $t = 0$
4 while $t < t^{\max}$
5 Determine the optimized quantization matrix
6 Update the quantization matrix, Q_m^+
7 $t \leftarrow t + 1$
8 End while
9 Return $[Q^*]$

5. Results and discussion

5.1. Dataset and procedure

The experimental study for the WE-OQM and the standard, as well as the improved entropy coding in HEVC standard, has been finished using the selected eight video sequences existing in http://www.cipr.rpi.edu/resource/sequences/sif.html in YUV file format. The information and number of frames available in eight video sequences are differentiated by mobile, container, coastguard, hall monitor, garden, tennis, foreman and football with 300, 140, 112, 300, 300, 300, 115 and 125 frame sequences respectively. The resolution at 352×288 for foreman, container, hall monitor, coastguard video sequences and 352×240 resolutions for mobile, football, tennis and garden. In order to understand the performance of encoded principle, the PSNR of the decoded video sequences is examined. The effectiveness of the WE-OQM method is estimated by comparing with the improved and standard encoding method. Here forth, the statistical performance comparison of the proposed method refers to WE-OQM with the existing method so called WE-encoding, and the standard encoding method is discussed in the following sections.

5.2. Quality of decoding

Here, the graph plotted between a number of transmitted bits and PSNR to analyze the performance of the WE-OQM method using PSNR metrics is presented and then compared the results with the standard entropy coding methods. Fig. 6 signifies the PSNR analysis for the video sequences such as football, garden, mobile, tennis, coastguard, foreman, hall monitor, and container. In Fig. 2 the PSNRs are plotted for varying number of transmitted bits, which are determined by means of block sizes, 2, 4, 8 and

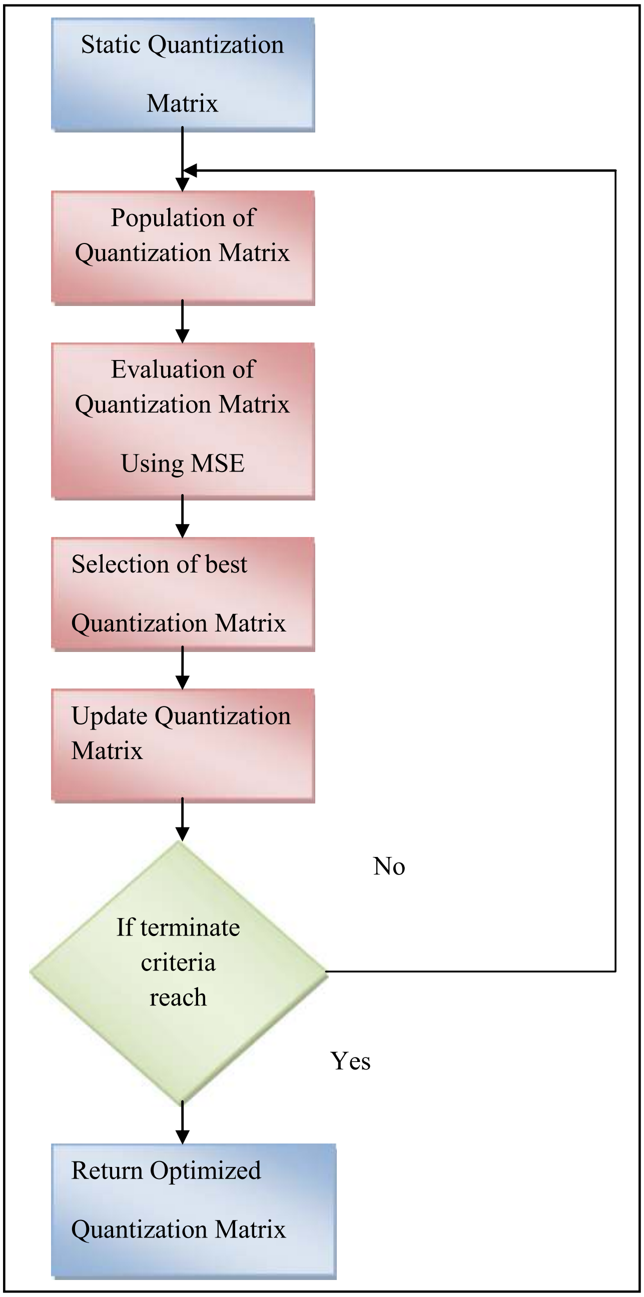

Fig. 4. Flowchart of Optimized QMs.

16. The proposed WE-OQM method meets the PSNR of 78 dB when transmitting at 1850 kbps and it is depicted in Fig. 6(a). In Fig. 6(b), the PSNR has been increased to around 78 dB, when transmitting at 2800 dB. In case of Fig. 6(c), the proposed WE-OQM outperforms the conventional methods and reaches 1900 kbps. The proposed WE-OQM method attains 73 dB and 79 dB when transmitting at 3950 and 2950 and it is demonstrated in Fig. 6(d) and (e). Moreover, the proposed method has managed to reach a maximum PSNR of 75 dB, and it depicts in Fig. 6(f). In Fig. 6(g) and (h), the proposed method achieves 84 dB and 83 dB respectively. The performance deviation value between the WE-OQM and the standard entropy methods are given as 13.7%, 5.5%, 6.3%, 10.9%, 8%, 5.3%, 5.4%, and 7.41% and the percentage deviation between WE-OQM and weighted entropy methods are given as 5.1%, 1.3%, 5.5%, 4.8%, 3.2%, 3.3%, 2.98% and 2.4% with respect to video sequences football, garden, mobile, tennis, coastguard, foreman, hall monitor and container. The minimum performance deviation value between the WE-OQM and the standard entropy methods have been attained by the foreman. Similarly, the garden has achieved minimum percentage deviation between WE-OQM and the weighted entropy methods (Fig. 5).

In case of a mobile video sequence, the performance of WE-OQM method is much lower than the existing weighted entropy method. It is because, it does not adapt with the encoded principle. Thus, the performance of the mobile video sequence is low than the other video sequences. In hall monitor video sequence, the WE-OQM and standard entropy method have attained the maximum PSNR of 84 dB and 79.5 dB, respectively.

Since the WE-Encoding exploits meta-heuristic search, it highly on the initial solution. In the rarest case, i.e., at 1500 kbps (approximately), the WE-Encoding provides an unusual rise in the PSNR value.

While the literature lags in optimizing the QM, we find the little relevance from the research contributions, FSDQ (Yin et al., 2015) and RDOQ (Karczewicz et al., 2008) in QM design. Hence, the comparison is made with them and quantified in Table 1. The average PSNR for the proposed WE-OQM is about 84% with respect to the Best case scenario. It can be seen that the proposed approach can attain slightly enhanced average video encoding performance than the conventional SDQ (Yin et al., 2015). Meanwhile, the PSNR rate is noted with respect to the RDOQ is enhanced much. In addition, one can see that the proposed method is able to attain slightly better performance compared with the WE-Encoding (Sunil Kumar et al., 2017).

As shown in Table 2, the performance of the WE-OQM method and its comparison with respect to the statistical measures namely mean, median, best, worst, and deviation are tabulated. These measures are calculated from the results of all decoded video sequences. That is to say, mean denotes the average PSNR of all the retrieved video sequences. Compared with the standard entropy method, the mean encoding performance of WE-OQM method improves 5.3%, 6.2%, 6.8% and 7.5% with the respective block sizes of 1, 2, 4 and 8. According to the median encoding performance with corresponding block sizes 1, 2, 4 and 8, 5.3%, 7%, 5.9% and 6.7% improvement is observed for the WE-OQM method. As per the best case scenario, the improvement of the WE-OQM over the standard entropy is noted as 5.5%, 5.7%, 6.7% and 5.9% with the corresponding block size of 1, 2, 4 and 8. While calculating the worst measure for the performance identification at varied block size 1, 2, 4 and 8, the WE-OQM method indicates better performance with 4.7%, 6.6%, 10.7% and 10.8% improvement. When considering the deviation measures, the better performance occurs for all block size. In addition, the deviation performance of WE-OQM method is far better than the standard as well as existing weighted entropy methods.

5.3. Computation overhead

Table 3 illustrates the computational time for the selected eight video sequences. The computational time experienced by the WE-OQM method is higher than the standard and weighted encoding principle in all video sequences. Due to more steps involved in WE-OQM HEVC encoding principle, the computational time increases. Moreover, Table 4 shows the performance of the WE-OQM method with respect to the computational time and PSNR for the selected eight video sequences. When comparing the WE-OQM encoding with the standard as well as weighted entropy method, the time required is high with proportion to the PSNR level. However, in block size 2 of video sequence 3, 6 and block size 1 of video sequence 3, the time incurred by the

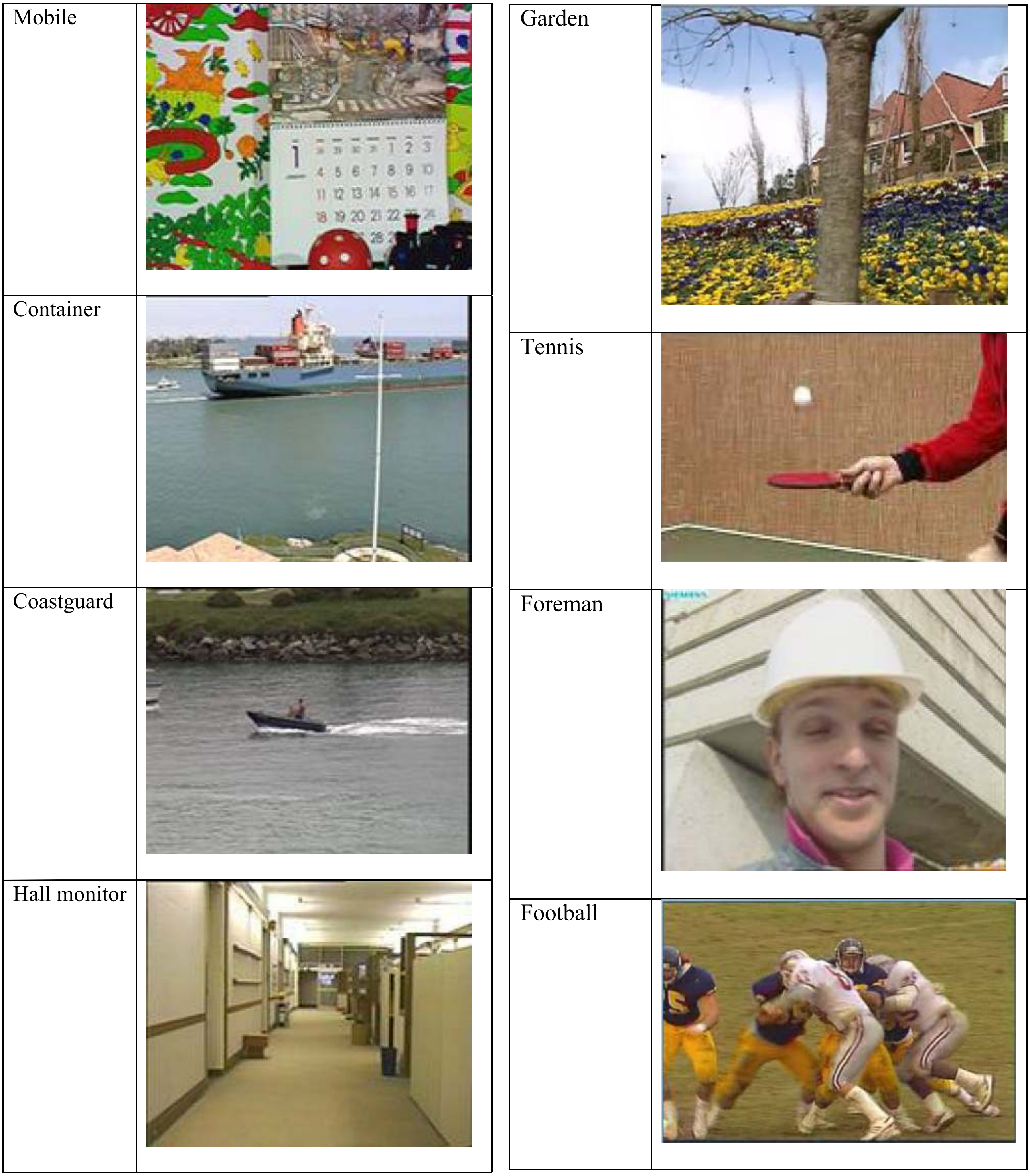

Fig. 5. Sample frames of eight video sequences.

WE-OQM method over standard entropy encoding is lesser than the WE-OQM method over existing weighted entropy method. Similarly, in block size 4 and 8 of video sequence 3, the PSNR values of the WE-OQM method over weighted entropy method are reduced than the WE-OQM over standard entropy method, and it is expressed as the negative sign. Even though complicated encoding steps are introduced, this has increased the efficiency of the WE-OQM method. The compression ratios of selected eight video sequences with the percentage reduction in a number of bits to be transmitted for WE-OQM over existing methods are tabulated in Table 5. It is clear that, the compression ratio (Zalik and Lukac, 2014; Murthy and Sujatha, 2016) of proposed WE-OQM is higher than the standard and existing methods for all selected eight video sequences. The compression ratio can be formulated as the ratio of number of actual bits to the number of bits transmitted as given in Eq. (15), whereas the reciprocal of compression ratio refers to the data rate savings as mentioned in Eq. (16).

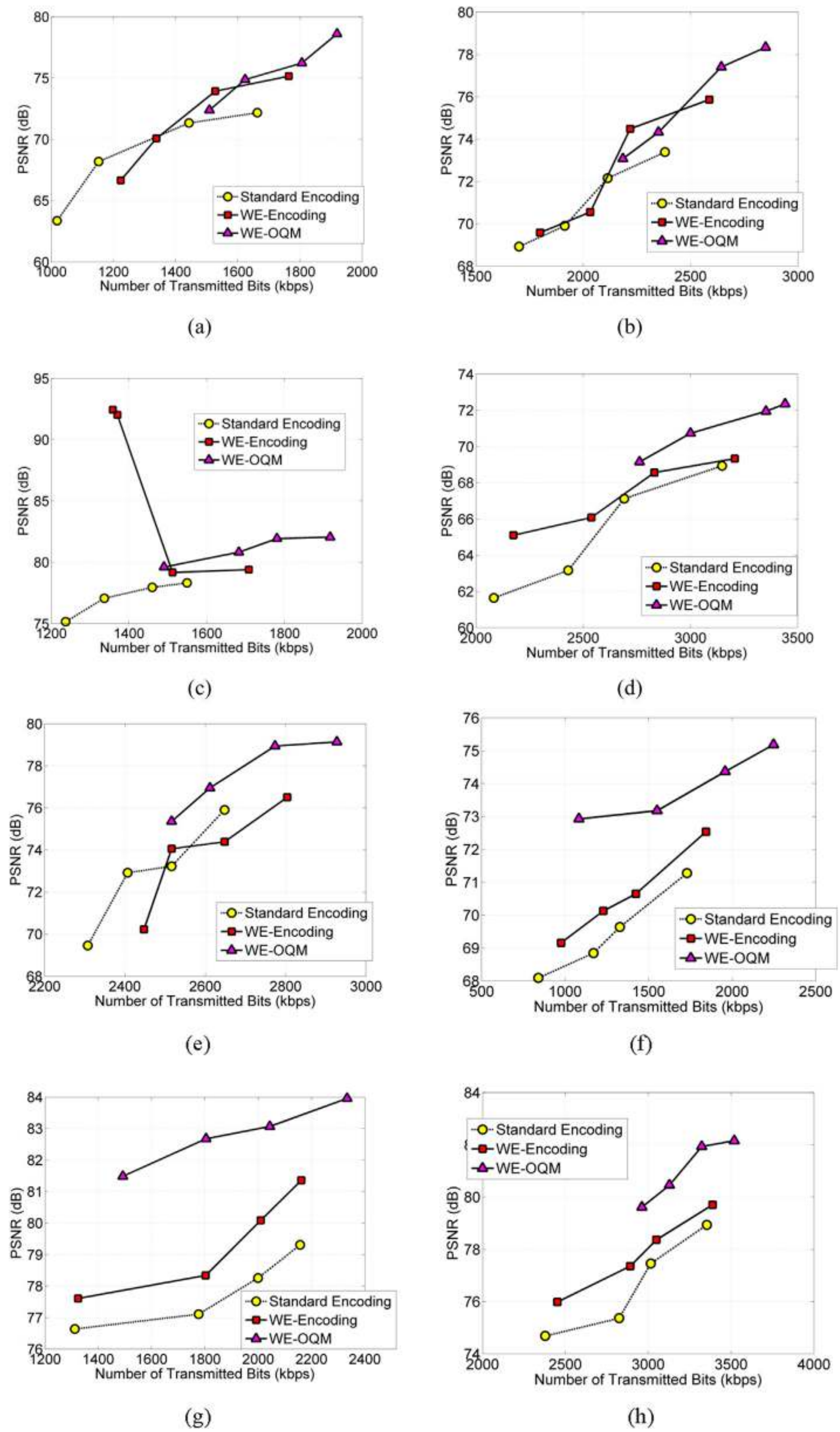

Fig. 6. PSNR of the decoded video sequences – (a) football, (b) garden, (c) mobile, (d) tennis, (e) coastguard, (f) foreman, (g) hall monitor, (h) container after transmitting through improved as well as standard entropy encoding principle of HEVC.

$$CR = \frac{\textit{Number of actual bits in the sequence}}{\textit{Number of compressed bits in the sequence}} \tag{16}$$

$$\%N = \frac{1}{CR} \times 100 \tag{17}$$

From Table 5 the performance comparison of WE-OQM over standard method in terms of compression ratio for the first and sixth video sequences are 35.29% and 62.5% improved with the corresponding data-rate savings of 3.41% and 7.24%. Despite this the overall performance of data-rate saving with regards to the com-

Table 1
Comparison of proposed and conventional methods for average psnr of the decoded video sequences.

Data Transmission (in kbps)	WE-OQM (Best Case)	WE-OQM (Worst case)	WE-OQ (Mean case)	WE-OQM (Median case)	WE-Encoding	FSDQ (Yin et al., 2015)	RDOQ (Karczewicz et al., 2008)
1000	80.03	66.32	72.1525	70.88	72.1525	33.05	31.95
1500	81.51952	67.7417	74.30541	72.71881	74.30541	34.05	32.975
2000	82.9987	68.30341	76.36477	76.27143	76.36477	35.05	34
2500	84.29837	68.86511	77.67508	77.38834	77.67508	35.575	34.5125
3000	85.31558	70.73516	79.34501	79.48154	79.34501	36.1	35.025
3500	86.33279	72.65128	80.63889	81.8767	80.63889	36.625	35.5375
4000	87.35	75.15	81.71625	82.79	81.71625	37.15	36.05

Table 2
Mean encoding performance of WE-OQM, WE and EE encoding principle of hevc (WE-OQM is the weighted entropy encoding with optimized quantization matrix, WE is the weighted entropy and EE is the entropy encoding).

Block size	Mean			Median			Best			Worst			Deviation		
	EE	*WE*	*WE-OQM*	*EE*	*WE*	*WE-OQM*	*EE*	*WE*	*WE-OQM*	*EE*	*WE*	*WE-OQM*	*EE*	*WE*	*WE-OQM*
1	74.79	76.24	78.98	74.65	76.19	78.88	79.31	81.36	83.96	68.94	69.34	72.36	3.91	3.98	3.84
2	73.4	74.96	78.23	72.69	74.44	78.18	78.26	80.09	83.07	67.13	68.57	71.95	4.14	4.08	3.97
4	71.57	74.83	76.76	71.41	72.31	75.91	77.11	92.03	82.68	63.17	66.09	70.74	4.92	8.06	4.21
8	69.75	73.35	75.46	69.19	69.91	74.22	76.64	92.45	81.49	61.65	65.11	69.16	5.49	8.82	4.35

Table 3
Computation time incurred by we-oqm, weighted and standard encoding principle of HEVC.

Block size	1			2			4			8		
Method	*Standard*	*Weighted*	*WE-OQM*	*Standard*	*Weighted*	*WE-OQM*	*Standard*	*Weighted*	*WE-OQM*	*Standard*	*Weighted*	*WE-OQM*
Sequence 1	3125492	3133454	4165237	3954164	3975798	4796544	4565415	4576468	5123697	4854611	4897649	5369747
Sequence 2	2564164	2574987	3456987	2665464	2667569	3496854	2748745	2765765	3956486	2965414	2965636	4123987
Sequence 3	4165445	4152343	4596984	4274642	4235496	4886583	4379577	4389465	4978892	4478989	4512485	5379151
Sequence 4	2477663	2545416	3346948	2577169	2671150	3569845	2698715	2714523	3784139	2736917	2764842	3928545
Sequence 5	4578152	4625414	5296424	4764423	4715649	5698414	4978548	4999496	5892445	5074643	5124414	6046545
Sequence 6	4639711	4641811	5144563	4781961	4758414	5426476	4871490	4941174	5969441	5063781	5124851	6046748
Sequence 7	4268954	4275151	5064746	4316474	4334741	5144878	4516574	4684715	5129648	4795716	4864841	5369744
Sequence 8	5127471	5145451	5578954	5295441	5384142	5796934	5299741	5348841	5894874	5397174	5434548	6047154

Table 4
Performance improvement of WE-OQMover standard and weighted encoding principle and the computation cost incurred for the improvement.

Comparison Scenarios	Block size	1		2		4		8	
	Improvement Metrics	*PSNR (dB)*	*Time (s)*	*PSNR (dB)*	*Time (s)*	*PSNR (dB)*	*Time (s)*	*PSNR (dB)*	*Time (s)*
Proposed Weighted Entropy Encoding with optimized QM versus standard Entropy Encoding	Video Sequence 1	8.92	33.27	6.85	21.3	9.81	12.23	14.23	10.61
	Video Sequence 2	6.74	34.82	7.28	31.19	6.32	43.94	6.02	39.07
	Video Sequence 3	4.76	10.36	5.11	14.32	4.88	13.68	5.93	20.1
	Video Sequence 4	4.96	35.08	7.18	38.52	11.98	40.22	12.18	43.54
	Video Sequence 5	4.26	15.69	7.8	19.6	5.53	18.36	8.49	19.15
	Video Sequence 6	5.49	10.88	6.79	13.48	6.29	22.54	7.11	19.41
	Video Sequence 7	5.86	18.64	6.15	19.19	7.22	13.57	6.33	11.97
	Video Sequence 8	4.08	8.81	5.78	9.47	6.75	11.23	6.6	12.04
Proposed Weighted Entropy Encoding with optimized QM versus Weighted Entropy Encoding	Video Sequence 1	4.6	32.93	3.11	20.64	6.85	11.96	8.6	9.64
	Video Sequence 2	3.26	34.25	3.92	31.09	5.34	43.05	5.02	39.06
	Video Sequence 3	3.34	10.71	3.49	15.37	-12.17	13.43	-13.88	19.21
	Video Sequence 4	4.36	31.49	4.93	33.64	7.04	39.4	6.22	42.09
	Video Sequence 5	3.44	14.51	6.12	20.84	3.9	17.86	7.3	17.99
	Video Sequence 6	3.65	10.83	5.27	14.04	4.35	20.81	5.45	17.99
	Video Sequence 7	3.2	18.47	3.72	18.69	5.54	9.5	5	10.38
	Video Sequence 8	3.07	8.42	4.56	7.67	4.01	10.21	4.78	11.27

pression ratio for the proposed WE-OQM holds higher than other existing methods. Besides the percentage reduction in number of bits to be transmitted for all eight video sequences is minimum than the standard entropy method and improved weighted entropy method. For 4 and 6 video sequences, the performance of percentage reduction in number of bits to be transmitted for standard as well as improved weighted entropy is 39.5%, 62.67% and 4.2%, 13.93% lesser than WE-OQM method respectively.

Table 5
Compression ratio with percentage reduction in number of bits to be transmitted for the improvement of WE-OQMover standard and weighted encoding methods.

Method	*Standard Encoding*		*WE-Encoding*		*WE-OQM Encoding*	
	CR	%N	CR	%N	CR	%N
Sequence 1	11	8.93	14	7.24	17	6.03
Sequence 2	8	12.93	9	10.65	10	10.07
Sequence 3	9	11.35	12	8.04	14	7.32
Sequence 4	5	20.37	8	12.87	8	12.33
Sequence 5	8	12.41	8	12.07	9	11.38
Sequence 6	9	11.09	21	4.81	24	4.14
Sequence 7	9	11.51	15	6.53	15	6.47
Sequence 8	6	17.36	8	12.09	9	11.73

CR – Compression Ratio, %N – Percentage reduction in number of bits to be transmitted.

6. Conclusion

In this paper, a novel optimized quantization matrix for HEVC coding standards was proposed. The selected standard video sequence has been experimentally examined, and the effectiveness of the WE-OQM method has been studied. The statistical measures such as mean, median, best and worst outcomes had been appraised for both the WE-OQM and the standard as well as improved encoding methods, and the overall percentage improvement of the WE-OQM method with the corresponding measures are 77.35%, 76.79%, 82.8% and 71.05%, respectively. In order to determine the encoding performance, the PSNR analysis has been studied where we had declared the performance of the WE-OQM encoding method. However the overall computation time of the WE-OQM method remains higher, the encoding performance is considerably higher than the previous method and so verified the significance of this optimized quantization matrix for the HEVC standard. Future work can be done in the direction of developing the motion models as well as optimizing the rate allocation for the motion information.

References

Tech, G., Chen, Y., Muller, K., Ohm, J.R., Vetro, A., Wang, Y.K., 2016. Overview of the multiview and 3D extensions of high efficiency video coding. IEEE Trans. Circuits Syst. Video Technol. 26 (1), 35–49.

Honrubia, A.J.D., Martinez, J.L., Cuenca, P., Gamez, J.A., Puerta, J.M., 2016. Adaptive fast quadtree level decision algorithm for H.264 to HEVC video transcoding. IEEE Trans. Circuits Syst. Video Technol. 26 (1), 154–168.

Sole, J., Joshi, R., Nguyen, N., Ji, T., Karczewicz, M., Clare, G., Henry, F., Duenas, A., 2012. Transform coefficient coding in HEVC. IEEE Trans. Circuits Syst. Video Technol. 22 (12), 1765–1777.

Nguyen, T., Helle, P., Winken, M., Bross, B., Marpe, D., Schwarz, H., Wiegand, T., 2013. Transform coding techniques in HEVC. IEEE J. Sel. Top. Signal Process. 7 (6), 978–989.

Hu, N., Yang, E.H., 2015. Fast mode selection for HEVC intra-frame coding with entropy coding refinement based on a transparent composite model. IEEE Trans. Circuits Syst. Video Technol. 25 (9), 1521–1532.

Yeh, C.H., Tseng, T.Y., Lee, C.W., Lin, C.Y., 2015. Predictive texture synthesis-based intra coding scheme for advanced video coding. IEEE Trans. Multimedia 17 (9), 1508–1514.

Wang, M., Ngan, K.N., Li, H., 2014. An efficient frame-content based intra frame rate control for high efficiency video coding. IEEE Signal Process. Lett. 22 (7), 896–900.

Han, W., Min, J., Kim, I., Alshina, E., Alshin, A., Lee, T., Chen, J., Seregin, V., Lee, S., Hong, Y., Cheon, M., Shlyakhov, N., McCann, K., Davies, T., Park, J., 2012. Improved video compression efficiency through flexible unit representation and systems for video technology. 20(12), 1899–1909.

Xiang, L., Wien, M., Ohm, J.R., 2011. Rate-complexity-distortion optimization for hybrid video coding. IEEE Trans. Circuits Syst. Video Technol. 21 (7), 957–970.

Correa, G., Assuncao, P., Agostini, L., Cruz, L.D.S., 2012. Performance and computational complexity assessment of high-efficiency video encoders. IEEE Trans. Circuits Syst. Video Technol. 22 (12), 1709–1720.

Bossen, F., Bross, B., Suhring, K., Flynn, D., 2012. HEVC complexity and implementation analysis. IEEE Trans. Circuits Syst. Video Technol. 22 (12), 1685–1696.

Sullivan, G., Ohm, J., Han, W.-J., Wiegand, T., 2012. Overview of the high Systems for Video Technology. 22(12), 1649–1668.

Sullivan, G.J., Boyce, J.M., Chen, Ying, Ohm, J.R., Segall, C.A., Vetro, A., 2013. Standardized extensions of high efficiency video coding (HEVC). IEEE J. Sel. Top. Signal Process. 7 (6), 1001–1016.

Choi, Yongseok, Choi, Jongbum, 2013. High-throughput CABAC codec architecture for HEVC. Electron. Lett. 49 (18), 1145–1147.

Zhou, Dajiang, Zhou, Jinjia, Fei, Wei, Goto, S., 2015. Ultra-high-throughput VLSI architecture of H.265/HEVC CABAC encoder for UHDTV applications. IEEE Trans. Circuits Syst. Video Technol. 25 (3), 497–507.

Shanableh, T., Peixoto, E., Izquierdo, E., 2013. MPEG-2 to HEVC Video transcoding with content-based modeling. IEEE Trans. Circuits Syst. Video Technol. 23 (7), 1191–1196.

Sun, Jun, Duan, Yizhou, Li, Jiangtao, Liu, Jiaying, Guo, Zongming, 2013. Rate-distortion analysis of dead-zone plus uniform threshold scalar quantization and its application—part II: two-pass VBR coding for H.264/AVC. IEEE Trans. Image Process. 22 (1), 215–228.

Sun, Heng, Gao, Shaoshuai, Zhang, Can, 2014. Adaptive bit allocation scheme for rate control in high efficiency video coding with initial quantization parameter determination. Signal Process. Image Commun. 29 (10), 1029–1045.

Miaohui Wang, King Ngi Ngan, Hongliang Li, Huanqiang Zeng, 2015. Improved block level adaptive quantization for high efficiency video coding. In: Proceedings of IEEE International Symposium on Circuits and Systems, 24–27 May, Lisbon, pp. 509–512.

Martin Winken, Andre Roth, Heiko Schwarz, Thomas Wiegand, 2015. Multi-frame optimized quantization for high efficiency video coding. In: Processings of Picture Coding Symposium, 31 May-3 June, Cairns, QLD, pp. 159–163.

Yin, Hai Bing, Yang, En-Hui, Yu, Xiang, Xia, Zhelei, 2015. Fast soft decision quantization with adaptive preselection and dynamic trellis graph. IEEE Trans. Circuits Syst. Video Technol. 25 (8), 1362–1375.

Malavika Bhaskaranand, Jerry D. Gibson, 2010. Spectral entropy based quantization matrices for H.264/AVC video coding. In: Processing of 2010 Conference Record of the Forty Fourth Asilomar Conference on Signals, Systems and Computers, 7–10 Nov, Pacific Grove, CA, pp. 421–425.

Li, Yuan-Xin, Yang, Guang-Hong, 2016. Adaptive asymptotic tracking control of uncertain nonlinear systems with input quantization and actuator faults. Automatica 72, 177–185.

Wang, C., Lee, S., Chang, L., 2001. Designing JPEG quantization tables based on human visual system. Signal Process. Image Commun. 16, 501–506.

Rodríguez-Vallejo, Manuel, Llorens-Quintana, Clara, Furlan, Walter D., Monsoriu, Juan A., 2016. Visual acuity and contrast sensitivity screening with a new iPad application. Displays 44, 15–20.

Sze, V., Budagavi, M., Sullivan, G.J., 2014. In: Quantization Matrix in High Efficiency Video Coding (HEVC): Algorithms and Architecture. Springer International Publishing, pp. 158–159.

Mannos, J.L., Sakrison, D.J., 1974. The effect of a visual fidelity criterion in the encoding of images. IEEE Trans. Inf. Theory 20, 525–536.

Zalik, Borut, Lukac, Niko, 2014. Chain code lossless compression using move-to-front transform and adaptive run-length encoding. Signal Process. Image Commun. 29 (1), 96–106.

Murthy, S.V.N., Sujatha, B.K., 2016. Multi-level optimization in encoding to balance video compression and retention of 8K resolution. Perspect. Sci. 8, 338–344.

Karczewicz, M., Ye, Y., Chong, I., 2008. Rate Distortion Optimized Quantization, document VCEG-AH21, ITU-T SG16/Q.6, Antalya, Turkey.

Sunil Kumar, B.S., Manjunath, A.S., Christopher, S., In Press. Improved entropy encoding for high efficient video coding standard. Alexandria Eng. J. Corrected Proof, Available online 3 November 2016.

Sullivan, G.J., Ohm, J.R., Han, W.J., Wiegand, T., 2012. Overview of the high efficiency video coding (HEVC) standard. IEEE Trans. Circuits Syst. Video Technol. 22 (12), 1649–1668.

Sunil Kumar B.S., Manjunath, A.S., Christopher, S., 2016. Inter Frame-Rate Distortion optimisation on scalable video for HEVC. In: 2016 International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), Bangalore, pp. 100–104.

Sunil Kumar, B.S., Manjunath, A.S., Christopher, S., Menon, Rajalaxmi, 2016b. Enhanced scalable video coding technique with an adaptive dual tree complex wavelet transform. Procedia Comput. Sci. 85, 70–77.

Sandeep, G.S., Sunil Kumar, B.S., D.J., 2015. An efficient lossless compressionusing double Huffman minimum variance encoding technique. In: 2015 International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Davangere, pp. 534–537.

Bhatnagar, Kavita, Gupta, S.C., 2016. Investigating and modeling the effect of laser intensity and nonlinear regime of the fiber on the optical link. J. Opt. Commun.

Rao Yarrapragada, K.S.S., Bala Krishna, B., 2017. Impact of tamanu oil-diesel blend on combustion, performance and emissions of diesel engine and its prediction methodology. J. Braz. Soc. Mech. Sci. Eng. 39 (5), 1797–1811.