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Low complexity encoder optimization for HEVC ☆

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A B S T R A C T

High Efficiency Video Coding (HEVC) improved the coding efficiency significantly. Compared to its predecessor H.264/AVC, it can provide equivalent subjective quality with more than 57% bit rate reduction. However, the improvement on coding efficiency is obtained at the expense of much more intensive computation complexity. In this paper, based on an overall analysis of computation complexity at the HEVC encoder, a low complexity encoder optimization scheme is proposed by reducing the number of available candidates for evaluation in terms of the intra prediction mode decision, early termination of coding unit (CU) splitting and adaptive reference frame selection. With the proposed scheme, the rate distortion optimization (RDO) technique of HEVC can be implemented in a low-complexity way for complexity-constrained encoders. Experimental results demonstrate that, compared with the original HEVC reference encoder implementation, the proposed optimization scheme can achieve more than 40% complexity reduction on average with coding performance degradation as only 0.43% which can be ignorable.

1. Introduction

The dramatically increasing of high definition (HD) and beyond-HD (e.g. 4k × 2 k or 8k × 4 k) videos are creating stronger demand of high efficiency video coding technology, which are beyond the capabilities of the state-of-the-art video coding standard such as H.264/AVC [1]. Therefore, the ITU-T Video Coding Expert Group (VCEG) and ISO/IEC Moving Picture Experts Group (MPEG) formed the Joint Collaborative Team on Video Coding (JCT-VC) in April 2010 to develop the new coding standard which is formally published in 2013 with the name as High Efficiency Video Coding (HEVC) [2] or H.265.

HEVC shows great improvement in many aspects. In [32], the authors provide an overview over the new characteristics which are likely to be used in HEVC in wireless environments and discusses several research challenges. Compared with the similar applications in H.264/264 [33], HEVC codec is more effective in both subjective and objective visual quality. In [31], the authors detail the HEVC applications in video transport and delivery such as broadcast, television over the Internet Protocol, Internet streaming, video conversation, and storage. It can be concluded that HEVC provides more flexible coding structure based on different system layer than those in H.264/AVC [34].

For the coding performance improvement, many new coding tools or coding structures are adopted or improved, which bring great performance improvement. Compared to its predecessor H.264/AVC, HEVC achieved more than 57% bit rate saving in terms of perceptual quality [3,4]. However, the improvement on coding efficiency is obtained at the expense of more intensive computation complexity. In [8,9], the authors analyzed the implementation complexity and the coding efficiency of these advanced coding tools in HEVC.

For evaluating the compression efficiency of each candidate configuration, the encoder usually employs the Lagrange multiplier optimization technique [6], which is expressed by

$$\min\{J\}\ J = D + \lambda \cdot R, \tag{1}$$

where J is the Lagrange rate–distortion (R–D) cost function to be minimized, D and R are the reconstruction distortion and entropy coding bits of a certain unit and λ is the Lagrange multiplier. The minimization process of the R–D cost is the well-known rate–distortion optimization (RDO). In general, to obtain accurate D and R, for each candidate, the encoder has to perform transform, quantization, entropy coding, inverse quantization, inverse transform, and pixel reconstruction, which makes the R–D cost calculation very time-consuming and brings great burden to the encoder implementation [7]. However, with the rapid developments of the portable devices, the discrepancy between the computationally intensive video codec and the limited computational capability of

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hardware platforms has become a bottleneck, especially in the real time visual communications. In view of these requirements, some researches on low complexity implementation of HEVC encoder have been done based on the new adopted coding tools or new coding structures.

For intra coding optimization of HEVC, many fast algorithms are proposed to reduce the coding complexity of intra mode decision. In [17], a partition depth prediction scheme is proposed based on the spatial correlation among adjacent prediction unit (PU). An adaptive threshold updating method is provided in order to improve the prediction accuracy. Due to the fact that the gradient can represent some characteristics of video content, in [18], a gradient based optimization scheme for intra mode decision is proposed. In [19], according to the correlation between the texture of video and the optimal mode, a fast intra mode decision method is presented. In [20], the authors proposed a fast intra mode decision for HEVC, in which micro level and macro level decision algorithms were presented. At the micro level, Hadamard transform based R–D cost is utilized to reduce the candidate number and an early rate distortion optimization quantization (RDOQ) skip method is also introduced to further reduce the coding complexity. At the macro level, an early coding unit (CU) split termination method is provided in terms of estimated R–D cost. In [21], a fast intra decision method is proposed to reduce the number of intra-prediction modes in rough mode decision (RMD) process based on direction information of the co-located neighboring block of previous frame along with neighboring blocks of current frame. In [22], according to analyze the distribution and changing trend of the costs generated by RMD, a fast intra decision scheme is presented to reduce the number of the candidates for the RDO process. In [17], Shen et al. proposed a fast scheme for intra coding in HEVC in order to determine the size of CU based on the depth of the surrounding CUs. Furthermore, a mode decision method is also provided for intra coding. in [30], variance based optimization scheme is incorporated for the intra coding optimization.

In HEVC, the most time consuming component is inter coding. For inter coding optimization, the researches mainly focus on the motion estimation and the quad-tree coding structure including CU, PU and TU. Many optimization schemes have been proposed. In our previous work [23], we propose an adaptive reference frame selection scheme to accelerate the motion estimation process. Since the CU splitting increases much complexity on HEVC, many optimization algorithms are proposed for the early termination of CU and determination of CU depth. In [25], the authors present a fast algorithm for early CU splitting and pruning according to a Bayes decision rule method. In [26], using the available side information such as sample adaptive offset (SAO) parameter values, PU sizes and coded block flag (cbf) data, a fast decision method of CU partition is proposed in order to reduce the coding complexity. In [24], based on the spatial and temporal correlation between the current CU and its adjacent and co-located CU, the authors proposed a fast algorithm which consists of splitting decision and termination decision for CU. For the early termination of CU splitting, a fast algorithm is proposed in [27] based on the energy of prediction residuals. In [11], an early TU decision algorithm for high efficiency video coding is proposed. In [12], coded block flag (cbf) is used to terminate PU encoding process. If the cbf of an inter PU in a CU is zero for luma and chroma except for inter NxN PU, the next PU encoding process for the current CU will be terminated. In [13], another scheme is proposed for skip mode early termination with the aim of optimizing the inter coding process. The basic idea is that if skip mode is the locally optimal mode of the current CU depth, skip mode is then considered to be global optimal mode and sub-tree computation process can be skipped. In [10], the authors proposed a complexity control algorithm for HEVC by adaptively choosing the CU splitting depth.

Though these techniques have shown good coding efficiency, the whole structure of the encoder has not been fully considered. In our previous work [29], we propose a low complexity rate distortion optimization scheme combining intra optimization and inter optimization to reduce the coding complexity of HEVC. In this paper, based on an overall analysis of computation complexity in HEVC encoder, we further improved the low complexity encoder optimization scheme for LDP (Low delay P) configuration of HEVC. Compared to our previous work, the main contributions mainly includes: in intra prediction, the gradient variance related to the video content is utilized to the speed up intra mode decision; in inter CU decision, the correlation between the rate distortion cost and CU splitting are exploited to accelerate the CU splitting termination process; and for reference frame selection, a probability model is proposed based on the spatial and temporal correlations among the adjacent frames and CUs, then the model is employed to shrink the RFS (Reference frame set) in order to reduce the inter coding complexity. The architecture of our scheme is shown in Fig. 1. It can be observed that our algorithms apply to the modules that require intensive computation in the encoder.

The rest of this paper is organized as follows. In Section 2, we first give an overall analysis of the computation complexity in HEVC encoder. Then the most time consuming modules in the HEVC encoder are analyzed in terms of the computational complexity and coding efficiency in details, including the block partitioning structure as well as inter and intra prediction in HEVC. In Section 3, we propose a low complexity RDO scheme for intra mode decision. In Section 4, a low complexity RDO scheme for inter coding is proposed including fast reference frame selection and inter CU splitting decision. Experimental results are provided in Section 5, and Section 6 concludes the paper.

2. Complexity analysis of HEVC encoder

2.1. Encoder computational complexity analysis

HEVC is based on traditional hybrid prediction/transform coding framework as described in Fig. 2 [3].

The newly adopted coding structure in HEVC offers more possibilities to split a frame into multiple units and more ways of combining different coding tools and parameters. Though this doesn't have significant impact on the decoder from the complexity aspect, it imposes a heavy computation burden to the encoder by fully leveraging its capabilities. Experiments are conducted to show the time consumption of the major modules in the encoder for Random Access and Low Delay configurations as illustrated in Table 1. It can be seen that the most time-consuming part is the motion estimation as a result of the multiple reference motion compensation.

For all-intra configuration, the coding complexity mainly comes from the mode decision from all available candidate modes. It can be seen from Table 2 that in the original configuration of HEVC, the percentage of intra coding complexity is over 80%. It can be also observed that when the number of intra prediction mode is reduced, the coding complexity can also be reduced much. E.g. when the number of mode candidates for PU with different size changes from the original S to different sets: S1, S2 and S3 as shown in Table 2, the coding complexity can be reduced by 8.50%, 16.0% and 25.7% respectively. Thus the number of candidates has crucial influence for the coding complexity. Moreover, it is reported that the full RD search of all available candidate modes will only achieve −0.4% coding gain, but bring about three times of the encoding time of the fast mode decision algorithm [14].

Based on the above considerations, in this section, the relationship between the compression efficiency and the corresponding

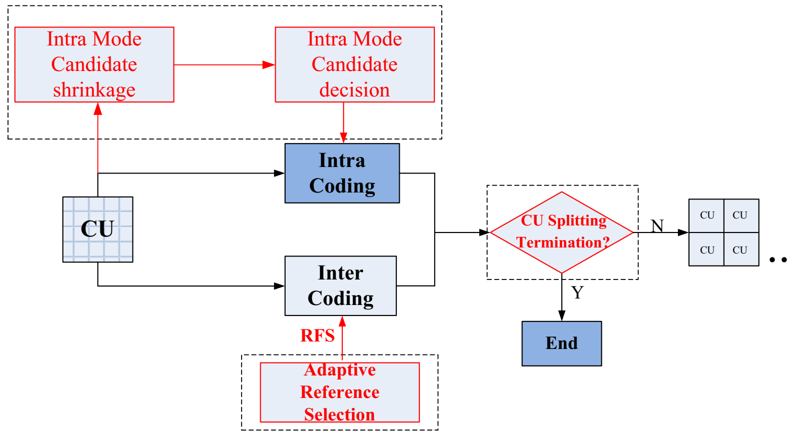

Fig. 1. The architecture of our proposed low complexity RDO scheme.

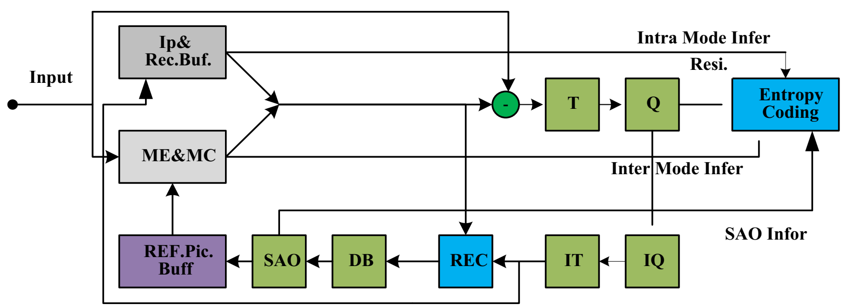

Fig. 2. HEVC hybrid coding framework, IP: Intra prediction, T: Transform, Q: Quantization, IT: Inverse Transform, IQ: Inverse Quantization, REC: Reconstruction, DB: Deblock-filter, ME: Motion Estimation, MC: Motion Compensation.

Table 1
Encoding time complexity analysis for each encoder module [%].

Test condition	ME	Transform	Entropy coding	In-loop filter	Others
RA-HE	69.78	13.65	3.49	3.64	9.44
RA-LC	72.24	13.74	3.54	0.15	10.33
LD-HE	76.93	11.62	2.96	1.2	7.29
LD-LC	77.94	11.28	2.97	0.11	7.7

Table 2
Encoding time complexity analysis with different number of candidate for PU with different size.

Test condition	Original (S)	S1	S2	S3
Candidate number	88333	66333	44222	22222
Percentage	82.1%	80.8%	78.9%	76.9%
complexity reduction		8.5%	18.0%	25.7%

computational complexity is characterized from the coding structure, intra and inter prediction aspects.

2.2. HEVC block partition structure

HEVC employs a highly flexible quad-tree coding structure based on coding tree unit (CTU), in which three new concepts named coding unit (CU), prediction unit (PU) and transform unit (TU) [5] are introduced to specify the basic processing unit of coding, prediction and transform. The highly flexible coding structure achieves a leap in coding performance and provides the encoder great flexibility to improve the coding efficiency.

The encoder selects the best coding tree structure, PU subdivision and residual quad-tree (RQT) configuration through exhaustive execution of RDO, which is a very time consuming process. Generally, the coding complexity of RDO in-creases monotonically with the depth of the CU partitioning since CU is the root of the PU partition and RQT. However, only limiting the depth of the CU partition is not sufficient to cope with the various local characteristics, as small CUs can be applied to the complex regions which large CUs cannot successfully cover. To address this issue, in Section 4, we propose an adaptive tree-pruning algorithm based on the properties of R–D cost of local prediction residuals.

2.3. Intra prediction

Compared with H.264/AVC, a significant change for intra prediction in HEVC is the use of more flexible block sizes (4×4 to 64×64) and more intra modes [14,16]. 33 angular prediction modes as well as planar and DC modes are supported at most. The increase of intra modes requires a good mode selection heuristics, since taking all the intra mode of each PU size into the RDO process will impose a great burden to the encoder. Therefore, the original HM reference software employs a fast RDO algorithm by combining the RMD and full R–D search together. However, the number of intra prediction mode is still large. This observation inspired us to further analyze the suitable number of intra prediction mode and make full use of the characteristic of video content

Table 3
Percentages of the first 3, 3, 2, 2 and 1 candidate direction to be the best direction.

CU Size	Class A (%)	Class B (%)	Class C (%)	Class D (%)	Class E (%)
64×64	58	60	51	95	65
32×32	83	81	84	86	84
16×16	84	84	85	83	88
8×8	87	87	87	86	91
4×4	83	81	79	80	86

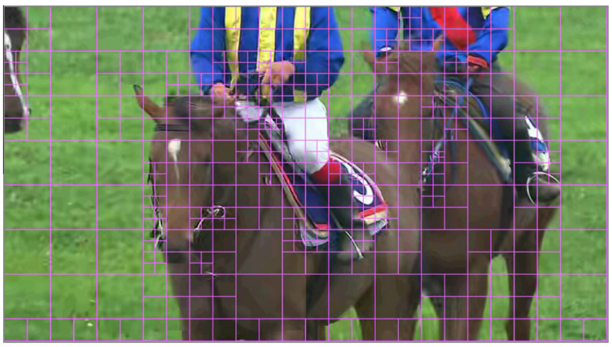

Fig. 3. The coding structure for a frame in RaceHoreses with HEVC.

to accelerate the intra mode decision, and a gradient based scheme to determine the number of candidate for intra mode decision is proposed in Section 3.

2.4. Inter prediction

For inter coding, similar to H.264/AVC, HEVC employs the block-based motion compensation (MC) with multiple reference pictures. However, due to the adopted advanced coding tools, inter coding in HEVC is more complex compared to H.264/AVC. For example, for sub-pixel interpolation, 8-tap DCT based separable interpolation filter (IF) is employed to generate the luma reference pixels for inter prediction, and for chroma component, 4-tap DCT-IF is applied. While in H.264/AVC, 6-tap interpolation filter is used for luma, and bilinear interpolation for chroma. Moreover, the number of motion search candidates in HEVC is multi times of that in H.264/AVC due to the advanced motion vector prediction (AMVP) in HEVC. And new coding modes, such as merge mode, also increase the complexity of motion estimation and motion compensation greatly due to the cross reference of the motion information of the spatial and temporal neighboring PUs.

The combination of the quad-tree coding structure and multiple reference pictures leads to the complexity of motion estimation increases linearly with the number of reference frames. However, it is generally believed that the correlations between two pictures are stronger when their temporal distance is small, and a straightforward way to reduce the complexity of motion estimation is to remove the long distance reference frames. However, it may result in evident R–D performance loss. To achieve high efficiency and low complexity motion estimation, in this paper, we will investigate how to manage the multiple reference pictures in the reference frame set (RFS) based on the spatial and temporal correlations among the adjacent frames and CUs.

3. Low complexity optimization for Intra coding

3.1. Gradient variance shrinkage scheme for the number of intra mode candidate

The determination of intra mode decision is to choose the coding mode with the minimal R–D cost, which can be represented as follows,

$$\theta_{opt} = \arg\min_{\theta \in \Omega}\{D_\theta + \lambda \cdot R_\theta\} \tag{2}$$

where Ω denotes the set of all the possible intra mode candidates. D_θ and R_θ are the distortion and bit rate for the prediction mode θ. The mode with minimum R–D cost will be determined as the optimal coding mode. However, performing all the possible modes greatly increases the coding complexity for HEVC. In [15], an improved intra coding optimization algorithm is provided to reduce the complexity for intra coding based on the Hadamard transform and the spatial correlation among the adjacent PUs. And the number of possible candidate modes to perform RQT process is reduced to 8, 8, 3, 3, 3 together with most probable modes (MPM) for PU with size of 4×4, 8×8, 16×16, 32×32 and 64×64, respectively. The scheme in [15] is adopted by HEVC with complexity reduction by 6% and 0.2% performance improvement. However, the number of modes to perform RQT is still too much. And video content characteristic is not fully considered. Table 3 shows the percentages of the first 3, 3, 2, 2 and 1 candidate intra mode in RMD to be the best coding mode. It can be seen that most PUs select the former ones to be the best coding mode.

In this subsection, a shrinkage scheme for the number of the candidate intra mode is proposed based on the gradient variance which can better reflect the video content characteristic.

The proposed shrinkage scheme can be formulated to be a problem to determine the number of prediction mode to perform RQT as following,

$$\Psi_N(\theta) = \underset{\theta \in \Omega}{\arg}\,\underset{N}{\min}\{J_{HAD}\} = \underset{\theta \in \Omega}{\arg}\underset{N}{\min}\{D_{SATD,\theta} + \lambda \cdot R_\theta\} \tag{3}$$

where $\Psi_N(\theta)$ denotes the set of the chosen N prediction modes. $D_{SATD,\theta}$ is the SATD (Sum of Absolute Transformed Difference) for the mode θ and R_θ represents the bit rate for coding the index of mode θ.

For nature video sequence, texture information of different areas varies much, which results in distinct properties within a frame. In HEVC, as illustrated in Fig. 3, the area with rare texture information tends to be coded as a big coding unit. While the area with rich texture information tends to be partitioned into smaller coding units.

Furthermore, for the area with rare texture information, the distribution of Hadamard based R–D cost is in accordance with the SSE based R–D cost. Fig. 4 shows the comparison between the Hadamard based R–D cost and SSE based R–D cost. The point with yellow color is the optimal mode for the PU. It can be observed that for the areas with rare texture information, the prediction mode with the smallest Hadamard based R–D cost has higher probability to the optimal prediction mode and thus less number of prediction mode is required.

In order to reduce the number of the candidate to perform RQT, we propose an adaptive scheme based on the gradient variance of the PU. Firstly, for each pixel in a given PU, the gradient is calculated as follows,

$$Grad(I_{i,j}) = |I_{i,j} - I_{i,j+1}| + |I_{i,j} - I_{i+1,j}| \tag{4}$$

where $I_{i,j}$ denotes pixel value with the position as (i,j). For the PU with size of $M \times M$, the gradient variance, Var_g is calculated as follows,

$$Var_g = \frac{1}{M^2}\left\{\sum_{i=1}^{M}\sum_{j=1}^{M}(Grad(I_{i,j}) - \overline{G})^2\right\} \tag{5}$$

where $\overline{G}$ is the average gradient of each pixel.

Based on the above observation, the number of candidate mode can be represented as a function of Var_g.

$$N = f(Var_g) = [N_h \cdot \alpha(Var_g) + 0.5] \tag{6}$$

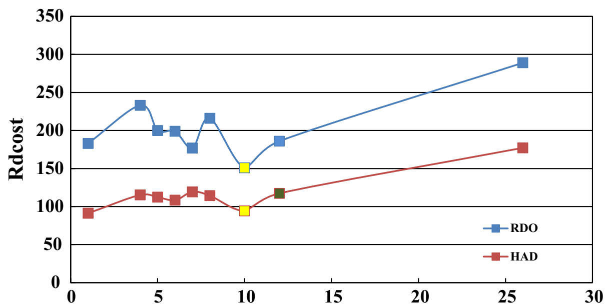

Fig. 4. The comparison of Hadamard based R–D cost with SSE based R–D cost.

where $\alpha(Var_g)$ denotes the shrink factor for the number of prediction mode which is related to the Var_g, N_h is the number of original intra mode in RMD and the function [] denotes the rounding operation.

$$\alpha(Var_g) = \begin{cases} 1 & Var_g > Th_1 \\ 3/4 & Th_1 \geqslant Var_g > Th_2 \\ 2/4 & Th_2 \geqslant Var_g > Th_3 \\ 1/4 & Var_g \leqslant Th_3 \end{cases} \tag{7}$$

In (7), the thresholds are updated adaptively from the previous coded frames as follows.

$$Th_i = \frac{1}{2^{i-1}} \cdot \frac{1}{N_j} \cdot \frac{1}{M^2} \cdot \sum_{r=1}^{N_j} Var^{Pre} \tag{8}$$

where N_j denotes the number of PU with the coding depth as j. Var^{Pre} is corresponding gradient variance.

3.2. Hadamard transform based mode candidate decision for intra coding

After determining the number of the intra prediction mode, the next step is to decide prediction mode set for RQT, especially when the number is smaller. The prediction mode set has key influence for the final coding performance. Thus, how to determine the set accurately is a crucial issue. In HEVC, Hadamard transform based scheme is utilized to estimate the R–D cost for the determination of prediction mode set as follows.

$$J_{HAD}(\theta) = SATD_\theta + \lambda \cdot R_{\theta,mode} \tag{9}$$

where $J_{HAD}(\theta)$ denotes the Hadamard transform based R–D cost, $R_{\theta,mode}$ indicates the bit rate for coding the prediction mode index. This method cannot reflect the true R–D cost especially when the texture information is rich for some coding units. In this paper, based on the analysis of the Hadamard transform based coefficients, we propose an improved scheme for the determination of prediction mode for intra coding.

Firstly, the Hadamard transformed coefficients, $C(i,j)$, are quantized as follows.

$$C'(i,j) = C(i,j) \gg ((QP-4)/6) \tag{10}$$

where $C'(i,j)$ denotes the quantized coefficients. QP is the quantization parameter.

Then the Hadamard based distortion, D_{HAD}, is defined as

$$D_{HAD} = \sum_{i=1}^{N} \sum_{i=1}^{N} C'(i,j) \tag{11}$$

Fig. 5 shows the correlation between the SSE and D_{HAD}. It can be seen that a linear correlation holds firmly between them with the intercept as zero. Thus the SSE can be represented in terms of D_{HAD} with a linear function as follows.

$$D_{SSE} = \alpha \cdot D_{HAD} \tag{12}$$

In order to further present the correlation between the Hadamard transform and DCT. We also investigate the correlation between the true bit rate, denoted as R_{SSE} and the non-zero quantized Hadamard transformed coefficients, denoted as $N_{HAD,nonzero}$, as illustrated in Fig. 6. It can be observed that the true bit rate for a coding unit can be represented by a linear correlation approximately. Considering the influence of bit rate of mode index, the Hadamard transform based estimation mode of the bit rate is presented as (13).

$$R_{SSE} = \gamma \cdot N_{HAD,nonzero} + R_{index} \tag{13}$$

Combine (12) and (13), the proposed Hadamard transformed based estimation of R–D cost can be modeled as (14). Then (14) can be utilized for the determination of prediction candidate mode.

$$J_{HAD} = \alpha \cdot D_{HAD} + \lambda_{mode} \cdot (R_{index} + \gamma . N_{HAD,nonzero}) \tag{14}$$

where α is a constant which is set to be 0.5 empirically.

4. Low complexity optimization for inter coding

In the above section, a fast intra optimization scheme is proposed to reduce the intra coding complexity. However, for video coding, inter coding consists the most coding complexity. In this subsection, we propose an optimization scheme for inter coding including early termination of CU splitting and fast reference selection.

4.1. Early termination of CU splitting

The flexible CTU based coding structure in HEVC brought great performance improvement but also with great coding complexity increasing. In this subsection, a fast CU splitting decision algorithm is presented for inter frame coding to reduce the inter coding complexity. We start with the motivating observations, which provide useful guidelines for modeling the correlation between CU splitting and rate distortion cost of prediction residuals in the current CU level. This correlation is employed to accelerate the CU splitting termination process for inter frame coding.

In video coding, prediction residuals can reflect the prediction accuracy. For temporally stationary and spatially homogeneous blocks, prediction residuals are relatively small, and large CU is more likely to be chosen as the optimal CU size. While small CU partition is preferred for objects with flexible motion since in such cases large CU can be hardly predicted accurately, and thus large prediction residuals need to be coded. Therefore, if the current CU size is sufficient for accurate prediction, there is no need for further splitting. On the contrary, if the residuals of current CU size are still large, further splitting might be necessary to get more precise prediction.

For CU splitting in HEVC, whether to split the current CU is determined by the comparison of the R–D cost to encode the prediction residual between the CU and R–D cost of its four sub-CUs. Fig. 7 shows the R–D cost distribution for the PU in the same depth with splitting and non-splitting. It can be seen that an evident line exists between the partitioned PU and non-partitioned PU. Therefore, it is reasonable to utilize the R–D cost of the prediction residuals to determine whether to perform splitting of the current CU. If the R–D cost is smaller than a predefined threshold, then the CU splitting can be early terminated. Thus a reasonable determination scheme of the threshold is necessary.

Traditionally, arithmetic mean is considered as an usual method for this situation. However, in this paper, it is not suitable since the R–D cost of some non-splitting CU is extremely large. If arithmetic mean is directly utilized, the value of the threshold will be much

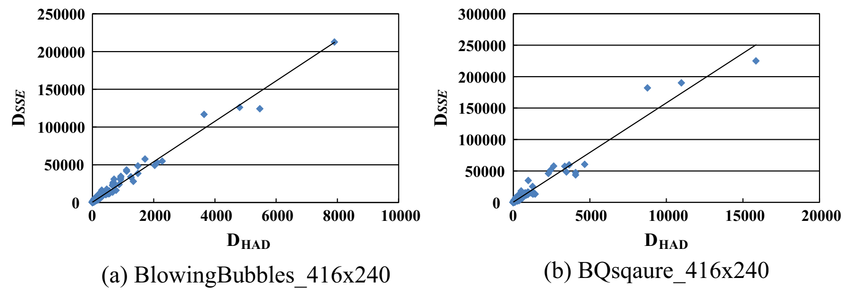

Fig. 5. The correlation between SSE and Hadamard based distortion.

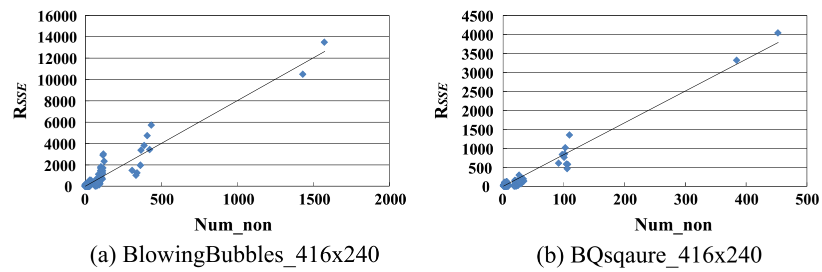

Fig. 6. The correlation between bit rate and Hadamard transform based non-zreo coefficients.

bigger. Then it can affect the accuracy of the determination of CU splitting. Thus in our paper, we adopt the K_ith minimum R–D cost as the threshold for the determination of CU splitting in ith depth.

$$K_i = round(k \times N_{rd}^i) \tag{15}$$

where N_{rd}^i is the number of non-splitting CU in ith depth. k belongs to 0 to 1.

R–D cost has much correlation with QP. For the given prediction residual, RD cost is much different for different QP. In LDP configuration of HEVC, in order to improve the coding efficiency, Rate-GOP is adopted in which the frames are divided into different depth and different QP is assigned. Then the frame depth should be also considered into the determination of the threshold. Based on the above analysis, the proposed threshold is presented as,

$$K_{i,j} = round(k \times N_{i,j}) \tag{16}$$

where $N_{i,j}$ is the number of non-splitting CU in different frame depth j and different CU depth i.

In the implementation, for the first Rate-GOP, the frames are encoded as conventional scheme as default in HM. Then the initial thresholds can be obtained. Then for the subsequent CU, after performing all the coding modes, if the R–D cost is over the predefined threshold, then the CU should be partitioned to the next depth.

An advantage of the proposed scheme of the threshold determination is that the k can be adjusted if needed. If more coding complexity needs to obtain, then k can be assigned a bigger value.

We summarize the CU splitting process of the proposed scheme in Fig. 8. Firstly, the frames in the first Rate-GOP are coded with the conventional mode decision process. Then for the given k, $K_{i,j}$ can be achieved and corresponding thresholds can be determined. Subsequently, for a CU, all the coding mode are performed. Then the R–D cost J is obtained. Compared with corresponding threshold, if it is smaller than the threshold, the recursive splitting process can be terminated; otherwise, we proceed to the next CU depth.

4.2. Adaptive reference frame selection

After completing the determination of CU partition, coding complexity can be reduced much. While for motion estimation, another aspect bringing coding complexity increasing is multi-reference frame selection. For a given PU, ME should be performed on each reference frame in reference frame set (RFS). The number of reference frame has great influence for the coding efficiency. Generally speaking, more reference frames can bring much performance improvement. However, the coding complexity increases monotonously with the number of reference frame. In this subsection, we propose an adaptive reference frame selection algorithm by shrinking the RFS to reduce the computational complexity of ME.

For a given PU, the proposed determination of RFS can be formulated to choose some successive frames with the number as s_i from the original RFS as follows,

$$N_{RFS} = opt(s_1, \ldots, s_r). \tag{17}$$

After performing the ME on the $(i-1)$th reference frame, a minimum R–D cost, $Cost_{i-1}$, can be achieved. Before performing ME on ith reference frame, the R–D cost on ith reference frame, $Cost_i$, can be presented as,

$$Cost_i = Cost_{i-1} + \Delta Cost_i. \tag{18}$$

If $\Delta Cost_i$ is zero or over zero, then ME on ith reference frame is redundant. However, it is impossible to achieve $\Delta Cost_i$ before performing ME on ith reference frame. If whether to early terminate ME can be determined before searching on ith reference frame according to an adaptive scheme, the coding complexity can be saved. In R–D sense, the determination of the optimal reference frame has great correlation with the distortion and the motion vector difference (MVD) in the previous reference frames. Based on this, in our paper, an estimation function to estimate the probability of $\Delta Cost_i$ as zero or over zero is proposed which is presented as,

$$P(\Delta Cost_i \geqslant 0) = \max f(Res_k, MVD_k) \ (k = 0, \ldots, i-1), \tag{19}$$

where Res_k and MVD_k denote the distortion per pixel and MVD on the kth reference frame, respectively. The formulation of f has key influence for the accuracy of reference frame selection which can be presented as: (1) if Res_i and MVD_i are beyond the predefined thresholds, Th_{res} and Th_{MVD}, then the probability is 0. (2) Otherwise it is computed as follows,

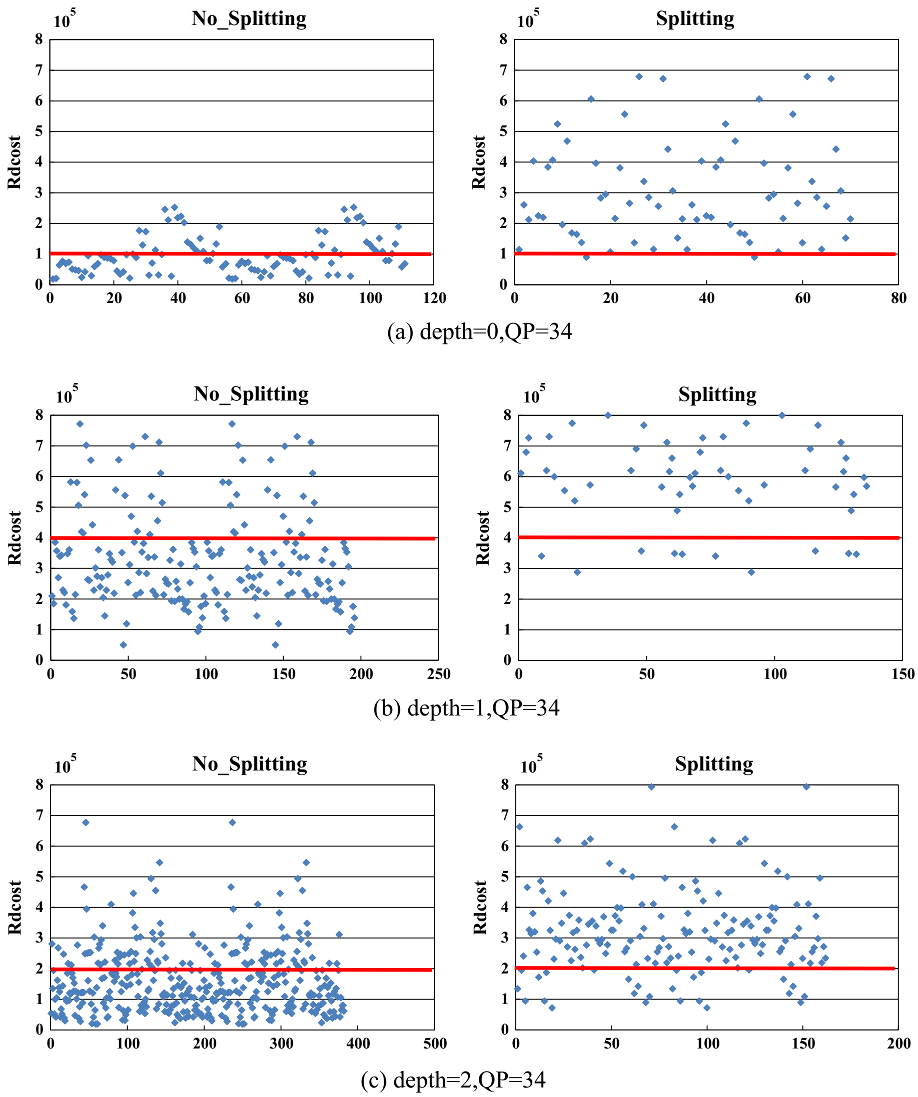

Fig. 7. The R–D cost distribution of CU with splitting on and off for the PU in the same depth.

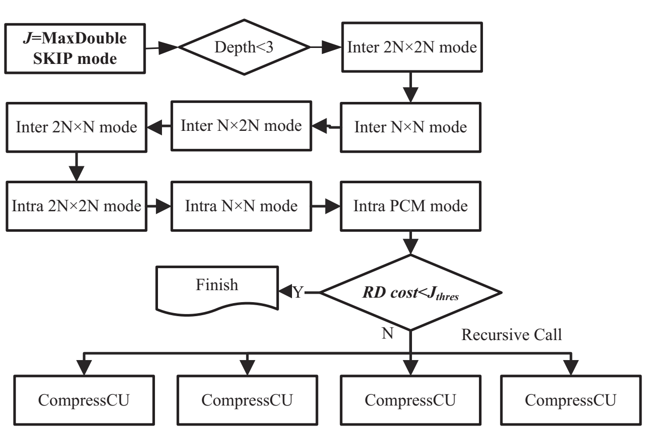

Fig. 8. Architecture of the proposed early termination of CU splitting scheme.

$$f(Res_k, MVD_k) = \beta_k \cdot \left(1 - \frac{Res_k}{Th_{Res}}\right) + \gamma_k \cdot \left(1 - \frac{MVD_k}{Th_{MVD}}\right). \tag{20}$$

However, how to incorporate (19) and (20) into the reference frame selection process is crucial for the coding performance. We will describe the proposed scheme from the following aspects.

(a) Reference frame distribution (RFD) based motion complexity.

In inter coding of HEVC, each frame in RFS has a different probability to be selected as the final reference frame. This probability is monotonically decreasing as the increase of the temporal distance, which can generate RFD. Table 4 shows the RFD for some adjacent frames of the sequence Kimono with low motion activity. The number of reference frame is set as four. It can be seen that the RFD of the PU in adjacent frames often has great similarity. And there is little probability variations of the frames in a temporal local window. While in some high motion sequences e.g. *BQSquare*, the RFD varies much as illustrated in Table 5. Consequently, RFD can characterize the motion complexity effectively.

Table 4
Reference frame distribution in *Kimono*.

POC	Ref0	Ref1	Ref2	Ref3
6	0.891	0.083	0.018	0.008
7	0.925	0.042	0.031	0.002
8	0.905	0.056	0.037	0.002
9	0.877	0.071	0.048	0.004

Table 5
Reference frame distribution in *BQSquare*.

POC	Ref0	Ref1	Ref2	Ref3
9	0.737	0.078	0.092	0.092
10	0.418	0.395	0.143	0.045
11	0.550	0.149	0.228	0.073
12	0.530	0.182	0.151	0.137

Based on the above analysis of RFD, a measurement of motion complexity called CME is defined as in (21).

$$C_{ME} = \sum_{i=1}^{s} \delta_i \times \left(N_i \Big/ \sum_{i=1}^{s} N_i \right). \tag{21}$$

where N_i denotes the count number of the ith reference picture referenced by the encoded PUs of the previous frame and the current frame. s indicates the number of reference frame and set to be 4 in the paper, and δ_i is the weighting factor which is determined by the temporal distance of the reference frames.

Considering the spatial correlation among the adjacent PUs in the same frame, C_{ME} is further modified as follows,

$$C_{ME} = \mu \times C_T + (1-\mu) \times C_S. \tag{22}$$

$$\mu = C_T/(C_T + C_S). \tag{23}$$

where C_T is the C_{ME} of the previous coded frame and C_S is the C_{ME} of coded PUs in the current frame based on (21). Parameter μ is the variable depending on C_T and C_S of the current PU.

Subsequently, we incorporate C_{ME} into the motion estimation process and propose an adaptive algorithm for multi-reference frame selection. The algorithm is proposed to adaptively adjust the number of reference frame in the RFS by the initial RFS determination, adaptive shrinkage of RFS and expansion of RFS as illustrated in the following aspects.

(b) Determination of Initial RFS.

As illustrated in Tables 4 and 5, for most PUs, the former reference frames in RFS have higher probability to be chosen as the final reference frame. Therefore, it is unnecessary to exhaustively search all of the reference frames for any PU. In our algorithm, we provide a suitable initial RFS based on C_{ME} to avoid the time consuming in motion estimation process in all the reference frames. After the C_{ME} is computed based on (21)–(23), the reference frame with reference index within C_{ME} consists of the initial RFS as shown in Table 6. Table 7 shows the proportion of the PUs in a frame to select the reference frame in the initial RFS as the final reference frame. It can be observed almost all PUs finish ME process in the initial RFS.

(c) Adaptive shrinkage of RFS.

Generally, most PUs will select the most suitable matching unit in the nearest reference frame, which motivated us to further shrink the RFS to reduce the computational complexity. When ME on the first reference frame is finished, the R–D cost on the next reference frame can be presented as,

$$Cost_1 = Cost_0 + \Delta Cost_1. \tag{24}$$

Then the proposed prediction model (19) and (20) is utilized to estimate the probability of the $\Delta Cost_i$ as 0 or over 0 as follows. If Res_0 and MVD_0 are beyond the predefined thresholds, Th_{Res_0} and Th_{MVD_0}, then the probability is 0. Otherwise, it is calculated by

Table 6
The mapping from C_{ME} to initial RFS.

C_{ME}	[1,2)	[2,3)	[3,4]
Inial RFS	0 1	0 1 2	0 1 2 3

Table 7
C_{ME} of different frames.

Sequence	Resolution	POC	C_{ME}	Initial RFS	Proportion (%)
Racehorse	416 × 240	6	1.5777	0 1	97.4
BQsquare	416 × 240	6	2.7984	0 1 2	95.5
PartyScene	832 × 480	6	2.6432	0 1 2	98.5
Kimono	1920 × 1080	6	1.2435	0 1	97.5

$$P(\Delta Cost_1 \geqslant 0) = f(Res_0, MVD_0) = \beta_0 \times \left(1 - \frac{Res_0}{Th_{Res_0}}\right) + \gamma_0 \times \left(1 - \frac{MVD_0}{Th_{MVD_0}}\right). \tag{25}$$

where β_0 and γ_0 are set as 0.5 and 0.5 empirically. Res_0 refers to the distortion of per pixel of the PU in the first reference frame which is calculated as follows,

$$Res_0 = D_0/S_0, \tag{26}$$

where D_0 refers to the distortion of the PU in the first reference frame and S_0 indicates the number of pixels of corresponding PU. The threshold Th_{MVD_0} is set as 2. The other threshold Th_{Res_0} is updated adaptively based on the CU depth as follows.

$$Th_{Res,0} = \frac{1}{C_s} \times \frac{Res_0^{Pre}}{N_0^{Pre}}, \tag{27}$$

where Res_0^{Pre} and N_0^{Pre} respectively denote the total distortion and total pixel number of the PU in the previous frame choosing the first reference frame as the final reference frame. When the probability calculated by (25) is beyond a given threshold, then ME can be early terminated. Otherwise, ME should be fully performed in the initial RFS.

(d) Expansion measures for RFS

With the proposed above early termination method, significant complexity reduction can be expected. However, a disadvantage of CME is that it converges to 1 with the number increasing of coding frames. So in our paper an expansion method is added by expanding the reference range from the within initial RFS to the outside of the initial RFS. Then above local optimization problem can be avoided.

The proposed expansion scheme can be presented as follows. When ME is terminated in the initial RFS, then the R–D cost for the next reference frame can be presented by

$$Cost_{C_{ME}+1} = Cost_{C_{ME}} + \Delta Cost_{C_{ME}+1}. \tag{28}$$

Then (19) and (20) is utilized to estimate the probability of the $\Delta Cost_{C_ME+1}$ as 0 or over 0 as follows. If Res_{C_ME} and MVD_{C_ME} are beyond the predefined thresholds, Th_{Res} and Th_{MV}, then the probability is 0. Otherwise, it is calculated

By

$$\begin{aligned} P(\Delta Cost_{C_{ME}+1} \geqslant 0) &= f(Res_{C_{ME}}, MVD_{C_{ME}}) \\ &= \beta_{C_{ME}} \times \left(1 - \frac{Res_{C_{ME}}}{Th_{Res,C_{ME}}}\right) + g_{C_{ME}}\left(1 - \frac{MVD_{C_{ME}}}{Th_{MV}}\right). \end{aligned} \tag{29}$$

Since for the reference frame with far temporal distance, distortion plays more important role than MVD. Thus, the parameter β_{C_ME} and γ_{C_ME} are set as 0.7 and 0.3 respectively. The thresholds in (29) are determined as like in (25).When the probability calculated by

Table 8
Coding performance of the proposed intra mode decision model [%].

Sequence	$N=1$	$N=2$	$N=3$	$N=4$	$N=5$	$N=6$	$N=7$	$N=8$
ClassA	−0.4	−0.4	−0.3	−0.3	−0.3	−0.3	−0.2	−0.2
ClassB	−0.4	−0.4	−0.3	−0.3	−0.3	−0.3	−0.2	−0.2
ClassC	−0.3	−0.4	−0.3	−0.3	−0.3	−0.2	−0.2	−0.2
ClassD	−0.3	−0.4	−0.3	−0.3	−0.2	−0.2	−0.2	−0.1
ClassE	−0.4	−0.4	−0.4	−0.3	−0.3	−0.3	−0.2	−0.2
Average	−0.3	−0.4	−0.3	−0.3	−0.3	−0.2	−0.2	−0.2

(29) is beyond a given threshold, then ME can be terminated. Otherwise, the RFS should be expanded to include the next reference frame.

5. Experimental results

In order to verify the efficiency of the proposed R–D optimization scheme, we incorporate the proposed scheme into the HM10.0. The complexity reduction is presented as follows

$$\Delta T = \frac{T_{anchor} - T_{pro}}{T_{anchor}} \times 100\%, \tag{30}$$

where T_{anchor} and T_{pro} denote the encoding time of original HM anchor and our proposed scheme respectively. When comparing the coding performance difference, we utilize the popular method proposed in [28] to calculate the difference between two R–D curves.

5.1. R–D performance for proposed intra optimization

In this subsection, experiments are performed to verify the coding efficiency of the proposed intra coding optimization scheme. Firstly, experiments are conducted to verify the efficiency of the proposed estimation mode as in Section 3.2. The results are illustrated in Table 8. The parameter α in (14) is set as 0.5 and γ is set as $1/\lambda_{mode}$. It can be seen that the proposed estimation mode can get better R–D performance when less number of prediction candidate modes is utilized. The maximum BD-rate reduction can be up to 0.4%. It indicates that the proposed scheme can contain the optimal prediction mode more accurately for intra coding.

Secondly, we perform experiments for the proposed shrinkage scheme as in Section 3.1 together with estimation mode as in Section 3.2 on the all intra (AI) testing configuration. The proposed shrinkage scheme can reduce the intra coding complexity. Meanwhile, the estimation mode can improve the intra prediction accuracy, especially when the number of intra prediction mode is less as illustrated in Table 8. In order to compare with the related schemes, the test sequences are default sequences by HEVC. Table 9 shows the R–D performance of the proposed scheme and performance comparisons with other related schemes. It can be seen that

Table 9
The R–D performance of proposed gradient based intra mode decision scheme and performance comparisons with other schemes.

	Pro		Ref. [18]		Ref. [19]	
	BD-rate (%)	ΔT (%)	BD-rate (%)	ΔT (%)	BD-rate (%)	ΔT (%)
ClassA	0.44	30.7	0.55	20.4	0.68	20
ClassB	0.40	25.9	0.70	20.5	1.20	21
ClassC	0.49	24.7	0.74	19.4	0.98	21
ClassD	0.59	26.8	0.94	19.5	1.45	19
ClassE	0.72	27.6	0.84	20.1	1.05	20
Average	0.52	26.6	0.75	19.9	1.07	20

Table 10
The comparison between HM anchor and proposed reference selection algorithm for LDP testing configuration.

Sequence	Resolution	Ref. [29]		Proposed	
		BD_rate (%)	ΔT (%)	BD_rate (%)	ΔT (%)
Akiyo	352 × 288	2.85	37.4	0.32	23.10
News	352 × 288	0.45	30.7	0.05	23.50
Salesman	352 × 288	0.48	19.5	0.02	17.20
Waterfall	352 × 288	2.15	15.2	0.06	14.40
Racehorses	416 × 240	0.50	21.3	0.47	28.40
Basketballpass	416 × 240	0.51	25.0	0.28	27.80
Crew	640 × 480	0.33	31.4	0.73	26.80
Ice	640 × 480	0.56	40.8	0.33	30.10
Soccer	640 × 480	0.32	29.2	0.35	26.40
Racehorses	832 × 480	0.22	14.9	0.47	29.50
BQmall	832 × 480	0.46	22.3	0.21	25.70
Fourpeople	1080 × 720	0.47	30.9	0.54	24.60
KristenAndSara	1080 × 720	0.70	33.9	0.28	26.70
Johny	1080 × 720	1.77	37.5	0.57	22.70
Vidyo1	1080 × 720	0.62	34.5	0.27	23.60
Vidyo3	1080 × 720	1.03	34.1	0.20	23.70
Vidyo4	1080 × 720	0.60	32.4	−0.06	25.60
Kimono	1920 × 1080	0.26	28.9	0.15	41.10
ParkScene	1920 × 1080	0.46	19.0	0.44	22.00
Cactus	1920 × 1080	0.38	20.3	0.43	24.40
BasketballDrive	1920 × 1080	0.34	25.1	0.60	28.70
PeopleontheStreet	2560 × 1600	0.48	25.1	0.37	27.00
Average		0.72	27.7	0.31	25.40

Table 11
The comparison between HM anchor and entire proposed inter optimization algorithm for LDP.

Sequence	Resolution	Ref. [29]		Proposed	
		BD_rate (%)	ΔT (%)	BD_rate (%)	ΔT (%)
Akiyo	352 × 288	3.23	58.7	0.19	48.50
News	352 × 288	1.53	49.1	0.81	44.60
Salesman	352 × 288	1.41	37.1	0.29	38.30
Waterfall	352 × 288	3.02	31.4	0.43	33.40
Racehorses	416 × 240	0.82	33.0	0.86	35.10
Basketballpass	416 × 240	0.59	31.7	0.00	39.10
Crew	640 × 480	0.57	40.7	0.74	38.20
Ice	640 × 480	0.58	51.5	0.65	46.00
Soccer	640 × 480	1.17	50.9	0.66	43.80
Racehorses	832 × 480	0.67	29.9	0.55	38.30
BQmall	832 × 480	0.96	37.1	0.43	33.60
Fourpeople	1080 × 720	1.10	47.5	0.37	46.60
KristenAndSara	1080 × 720	0.82	49.5	0.25	47.00
Johny	1080 × 720	2.28	52.6	0.10	46.40
Vidyo1	1080 × 720	1.13	53.5	0.25	47.00
Vidyo3	1080 × 720	1.42	54.4	0.43	50.50
Vidyo4	1080 × 720	1.15	51.0	0.33	46.00
Kimono	1920 × 1080	0.81	45.9	0.43	53.30
ParkScene	1920 × 1080	0.76	32.0	0.51	34.20
Cactus	1920 × 1080	0.88	36.3	0.50	38.70
BasketballDrive	1920 × 1080	0.40	33.7	0.84	36.50
PeopleontheStreet	2560 × 1600	0.76	31.7	0.60	35.40
Average		1.18	42.7	0.43	40.90

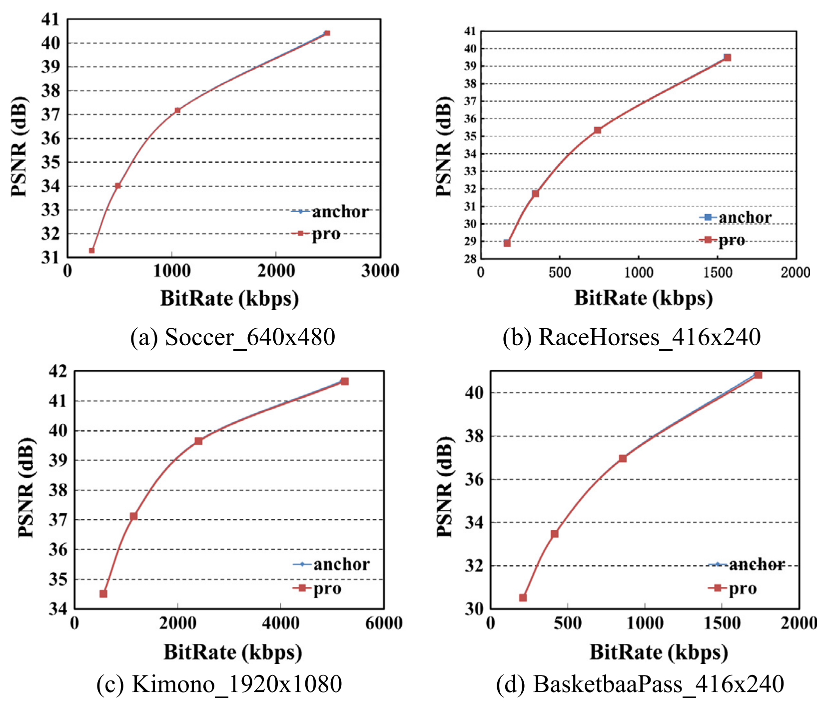

Fig. 9. R–D curve comparison for different sequences in LDP.

our proposed scheme can reduce the complexity by over 26% on average with only 0.52% BD-rate loss.

5.2. R–D performance for proposed adaptive reference selection scheme

We implement the experiments in LDP configuration to verify the efficiency of the proposed adaptive reference frame selection scheme. The number of reference frame is set to be 4 as default. The parameters α_i in (21) are defined as 1, 2, 3 and 4 respectively. If the probability by (25) and (29) is beyond 0.6, ME can be early terminated. The experimental results are presented in Table 10. From the table, it can be observed that the proposed adaptive reference selection scheme can reduce the coding complexity by 25.4% on average with small bit rate increasing as 0.31% averagely. Compared with our previous work in [29], the performance loss is reduced by much but with comparative complexity reduction.

5.3. R–D performance for proposed low complexity optimization

In order to verify the performance of the proposed entire low complexity optimization scheme, including fast intra coding, early

Fig. 10. Visual quality comparison for different sequences.

termination of CU splitting and adaptive reference frame selection, Table 11 provides the R–D performance as well as the complexity reduction. It can be observed that the proposed low complexity R–D optimization scheme can reduce the coding complexity by 40.9% on average with the increased BD-rate as only 0.43%. Compared with our previous work in [29], the coding performance has been improved much but with comparative complexity reduction. Furthermore, it can be seen that, compared with the performance of Table 10, the R–D performance loss is reduced for some sequences, e.g. *Fourpeople* and *Vidyo*1. It indicates that the proposed reference frame selection scheme and the CU splitting scheme can be combined together efficiently to reduce the coding complexity while retaining small performance loss. The reasons can be attributed to that the proposed scheme can reduce the side information to encode.

Fig. 9 shows the R–D curve comparisons between HM anchor and the proposed scheme. It can be seen that the two curves are almost the same under different bit rate and the performance degradation can be almost neglected.

In order to further present the coding efficiency of the proposed entire low complexity optimization scheme, Fig. 10 provides the visual quality comparisons for some different sequences, including the videos with rich texture information, edge information and motion information. It can be seen that the videos by our proposed optimization scheme has little difference with the sequences achieved by HM anchor.

6. Conclusions

This paper proposes a low complexity way to implement the HEVC encoder by accelerating the RDO process. The novelty of this paper lies in that, three techniques which aim to optimize the encoder in a rate distortion sense, are employed to reduce the computational intensive processing in intra mode selection, CU decision and reference frame selection. This paper demonstrates that the computational complexity can be greatly reduced at practically little coding efficiency loss in HEVC. The results and insights of this paper also provide valuable information for the implementation of practical real-time codecs to meet the limitations of power consumption.

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