Hybrid All Zero Soft Quantized Block Detection for HEVC
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Abstract—Transform and quantization account for a considerable amount of computation time in video encoding process. However, there are a large number of discrete cosine transform coefficients which are finally quantized into zeros. In essence, blocks with all zero quantized coefficients do not transmit any information, but still occupy substantial unnecessary computational resources. As such, detecting all-zero block (AZB) before transform and quantization has been recognized to be an efficient approach to speed up the encoding process. Instead of considering the hard-decision quantization (HDQ) only, in this paper, we incorporate the properties of soft-decision quantization into the AZB detection. In particular, we categorize the AZB blocks into genuine AZBs (G-AZB) and pseudo AZBs (P-AZBs) to distinguish their origins. For G-AZBs directly generated from HDQ, the sum of absolute transformed difference-based approach is adopted for early termination. Regarding the classification of P-AZBs which are generated in the sense of rate-distortion optimization, the rate-distortion models established based on transform coefficients together with the adaptive searching of the maximum transform coefficient are jointly employed for the discrimination. Experimental results show that our algorithm can achieve up to 24.16% transform and quantization time-savings with less than 0.06% RD performance loss. The total encoder time saving is about 5.18% on average with the maximum value up to 9.12%. Moreover, the detection accuracy of larger TU sizes, such as 16 × 16 and 32 × 32 can reach to 95% on average.

Index Terms—DCT, all zero block (AZB) detection, soft-decision quantization, rate-distortion modeling.

I. INTRODUCTION

THE state-of-the-art video coding standard High Efficiency Video Coding (HEVC) [1] jointly developed by the ISO/IEC MPEG and ITU-T, has achieved significant coding efficiency improvement compared with H.264/AVC [2]. The superior coding performance originates from the advanced coding tools adopted in HEVC, including quad-tree partition, extended-size discrete cosine transform (DCT) and additional discrete sine transform (DST) [3], etc. DCT is a vital but time-consuming module in HEVC, due to the computational burden of transform and the exhaustive rate-distortion optimization (RDO) process. However, in the case that one transform unit (TU) including non-zero residual data is identified as zero block after forward transform and quantization, there will be no subsequent entropy coding for RDO. In practice, there are a multitude of TUs to be quantized into all zero coefficients, especially for the small size TUs such as 4 × 4 and 8 × 8 in the low bit rate coding scenario. Thus, the all zero block (AZB) early determination ahead of transform tends to be useful for saving encoding time caused by redundant transform and quantization.

In literature, there have been a number of all zero block detection technologies [4]–[27] proposed for H.264/AVC and HEVC, aiming to accurately detect the AZB early with low complexity. Similar to early determination of CU splitting algorithms which are implemented with very different ways, such as [28] and [29], various AZB detection methods are designed to save encoding time in RDO process as well. Xuan et al. [4] derived the upper bound of the sum of the absolute difference (SAD), and determined the block as AZB if the SAD of the coding block is below the upper bound. The threshold value of the upper bound is theoretically derived based on the relationship between SAD and DCT coefficients. The similar idea based on SAD can also be found in [5]–[16]. In [5], the quantization parameter (QP) has been introduced to assist the threshold design. The detection method proposed in [17] refined the SAD threshold condition depending on the position of DCT coefficients to improve the detection accuracy. In [18], more sufficient and specific conditions are derived for three types of transforms, including integer 4 × 4 DCT for all the 4 × 4 blocks, Hadamard transform for 4 × 4 Luma DC coefficients and intra 16 × 16 blocks, and Hadamard transform for 2 × 2 Chroma DC coefficients.

Another method to improve detection accuracy with the consideration of frequency characteristics has been proposed in [19], where the sum of the squares is used to check AC energy of the residual data. However, the sum of squares should be calculated with multiplications which increase the computation burden in AZB detection in turn. Wang et al. [20], [21] further improved the AZB detection in [18] by utilizing a hybrid model for zero quantized
DCT coefficients to further reduce redundant computations. However, the AZB detection conditions derived by above methods cannot be applied straightforwardly when the Hadamard transform is enabled in H.264/AVC coding, such that the sum of absolute transformed different (SATD) is used instead of SAD in [22]. In addition, the AZB detection in [23] utilized the Hadamard coefficients to evaluate the zero blocks and there is hardly any extra computation cost since the Hadamard coefficients can already be obtained in the prediction stage. However, the detection accuracy may suffer from the difference between Hadamard and DCT transform.

Regarding HEVC, larger transform block sizes are employed compared with H.264/AVC, such as 16×16 and 32×32, which comprise more complex and diverse content characteristics. This brings new challenges to AZB detection as well, since the AZB detection methods in H.264/AVC are not appropriate to be straightforwardly applied in HEVC. In view of this, several AZB early detection approaches have been designed for HEVC structure. In [24], the genuine zero block (GZB), which represents the blocks identified as AZB right after hard-decision quantization (HDQ), is detected by extending the method in [23]. For larger TU sizes, i.e., 16×16 and 32×32, the AZB is examined through the DC coefficients of each 8×8 Hadamard transformed sub-block, and these DC coefficients are transformed by 2×2 and 4×4 Hadamard transform again. Moreover, Lee et al. [24] proposed a method to determine the pseudo zero blocks (PZBs), which denote the blocks quantized as non-zero blocks are finally forced to be AZBs by RDO. Although the AZB detection rate has been increased by combining multiple 8×8 Hadamard transform matrices to detect AZB for 16×16 and 32×32, it decreases the effectiveness for small TUs, and has the limitations in practice due to the empirical values introduced in the RD cost calculation. Wang et al. [25] provided an efficient AZB detection method for HEVC with sufficient conditions. However, this method only targets at the 4×4 block size. Recently, state-of-the-art AZB detection methods were proposed in [26] and [27]. In [26], the upper and lower bounds of SATD and one SATD threshold were used to detect GZB. For PZB, a fast rate-distortion cost estimation scheme was proposed in order to improve the detection rate. However, several empirical values were introduced in the GZB detection and the proposed distortion and rate estimation models in RDO for PZB determination tend to be sensitive to the initial values. The AZB detection proposed in [27] introduced the idea that the DCT coefficients can be approximated by multiplying the sparse matrix with the Walsh Hadamard transform (WHT) matrix. Based on the SATD and WHT coefficients, the AZB detection works without performing actual DCT and quantization. However, the detection rates for the 16×16 and 32×32 block size are not satisfactory since the approximated coefficients cannot well match the DCT coefficients.

For soft-decision quantization (SDQ), the final quantized coefficients are not only dependent on how the coefficients are quantized, but also rely on how these coefficients are entropy coded. The quantized coefficient becomes the free parameter to be optimized with the RDO, which provides more flexibilities in the AZB detection process. Therefore, it is difficult to directly infer the AZB conditions from the block features such as residual energy or SATD. Recently, Yin et al. [30] proposed an detection method based on more accurate zero-quantized deadzone offset model in Rate Distortion Optimized Quantization (RDOQ). Their previous work [31] also presented a detection method based on RDOQ. However, Although the characteristics of AZB after RDOQ were taken into account, research on the relationship between AZB and RD cost is still required. In this paper, we make further efforts to solve the AZB detection problem by jointly considering the HDQ and SDQ. Specifically, the conditions of AZB for HDQ are firstly derived, followed by the strategies for SDQ to further identify the blocks that are required to be quantized to AZB in the sense of RDO. In particular, in the identification of AZB with SDQ, the maximum transform coefficient amplitude is detected within the low frequency part of TU, and the rate and distortion estimation models are established based on the transform coefficients and SATD of blocks to further detect the AZB in the RDO framework.

The remainder of this paper is organized as follows. In Section II, the relative works on AZB detection are reviewed. The proposed AZB detection scheme is introduced in Section III, and the experimental results are provided in Section IV. Finally, Section V concludes this paper.

II. RELATIVE WORKS

Generally speaking, many block level features have been adopted as criterions to determine the AZB, such as residual energy, SAD and SATD of the given residual block. In particular, for the residual data z(x, y) in the given N×N transform block, the transform coefficient Z(u, v) can be described as follows based on the integer DCT transforms,

\[ Z(u, v) = \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} z(x, y) \cdot A(x, u) \cdot A(y, v) \]  

(1)

where,

\[ A(m, n) = \left[ \frac{\sqrt{2}}{N} \cdot a(m) \cdot \cos \left( \frac{2n + 1}{2N} \cdot m \pi \right) \right] \]

(2)

\[ m, n = 0, 1, \ldots, N - 1 \]

and

\[ a(m) = \begin{cases} \frac{1}{\sqrt{2}} & m = 0 \\ 1 & m = 1, \ldots, N - 1 \end{cases} \]

(3)

In the Dead Zone plus Uniform Threshold Quantization (DZ+UTQ), the transform coefficients Z(u, v) are quantized as L(u, v),

\[ L(u, v) = \text{sign}(Z(u, v)) \cdot (|Z(u, v)| \cdot M_{QP/6} + \text{offset}) \gg Q_{bits} \]

(4)

where \(M_{QP/6}\) is the multiplication factor equal to \(2^{Q_{bits}} / Q_{step}\), and \(Q_{step}\) denotes the quantization step which is associated
with the quantization parameter (QP). In practical implementation, the DZ+UTQ can be formulated by Eq.(4) with the \( M_{QP/6} \), \( \text{offset} \), and \( Q_{bits} \) defined as:

\[
M_{QP/6} = \{26214, 23302, 20560, 18396, 16384, 14564\},
\]

\[
\text{offset} = \begin{cases} 
171 \ll (Q_{bits} - 9), & \text{for I slice} \\
85 \ll (Q_{bits} - 9), & \text{for P/B slice}, 
\end{cases}
\]

\[
Q_{bits} = 29 + QP/6 - \text{bitDepth} - \log_{2}N,
\]

where \( \text{bitDepth} \) is the bit depth of input image pixel and \( N \) denotes the TU width. If the block is detected as AZB, it implies all the quantized coefficients \( L(u,v) \) should satisfy:

\[
|L(u,v)| < 1.
\]

Then we have

\[
|Z(u,v)| < Th(u,v), Th(u,v) = \frac{2Q_{bits} - \text{offset}}{M_{QP/6}},
\]

where \( Th(u,v) \) denotes the threshold of AZB. In the previous work, SAD in the residual domain is frequently used to detect the AZB. In particular, the detection condition is defined as:

\[
\text{SAD} < \Gamma (Th(u,v)),
\]

where \( \Gamma (\cdot) \) denotes the function based on \( Th(u,v) \) and it has been derived in various fashions [20], [25], [32]. However, the SAD value implies the residual difference in the residual domain, which cannot directly reflect the AZB characteristics. As such, in order to approximate the DCT coefficients in frequency domain, the Hadamard transform is applied to substitute the integer DCT transform such that the SATD from the Hadamard transform naturally becomes an alternative feature for AZB detection. However, although the SATD-based detection is able to improve the detection accuracy to some extent, previous works [24], [26] indicate that it may suffer from the undesirable detection rate for larger TU sizes due to more diverse content characteristics within one TU.

III. THE PROPOSED AZB DETECTION

In this section, we propose the AZB detection scheme for all sizes of TUs based on both mathematical derivations and empirical analyses. In HEVC reference software, the SDQ strategy-Rate Distortion Optimized Quantization (RDOQ) is performed by default after transform. In contrast with DZ+UTQ, RDOQ is able to determine the optimal quantized transform coefficients from the perspective of coding performance, which may result in some transform blocks which are non-zero blocks after DZ+UTQ actually quantized to AZB by RDOQ. Therefore, in this work, the AZBs are categorized into genuine all zero block (G-AZB) and pseudo all zero block (P-AZB) according to different quantization strategies, as shown in Fig. 1. In particular, the G-AZB denotes the block quantized to all zero coefficients after DZ+UTQ. Otherwise, if the non-zero coefficients in the transform block are further quantized to all zero coefficients by RDOQ, such block is regarded as P-AZB. The AZB distributions of each type for different TU layers are illustrated in Fig. 2. Obviously, we can see that the percentages of AZB blocks including G-AZB and P-AZB types increase monotonously with QP. Moreover, for the larger TUs such as 32×32 TU, there is hardly any G-AZB even for high QP cases. As such, in 32×32 TU, almost all the AZBs are P-AZBs, which implies there is slight possibility that the 32×32 TU is finally quantized to AZB without RDOQ. In other words, RDOQ contributes significantly to determine AZB blocks in this scenario. This motivates us to deal with G-AZB and P-AZB sequentially. In addition, as the residual coefficients of intra block tend to be larger even under the large QP values, here we only focus on the TUs from inter prediction.

A. Transform Specification

DCT has been proved to be an efficient transform method used in video/image compression, but the computational complexity is much higher than Hadamard transform. To reduce the computational cost of DCT, for the 8×8 and 4×4 transform blocks, the DCT transform cores are able to be simulated with Walsh-ordered Hadamard transform core and the sparse matrix \( A \) [27] with:

\[
DCT_N = \frac{1}{\sqrt{N}} A_N H_{w,N}.
\]
Specifically, sparse matrix $A$ is defined as:

$$A_8 = \begin{bmatrix}
64 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 58 & 0 & 24 & 0 & -5 & 0 & 12 \\
0 & 0 & 59 & 0 & 0 & 0 & 25 & 0 \\
0 & -20 & 0 & 49 & 0 & 33 & 0 & 14 \\
0 & 0 & 0 & 0 & 0 & 64 & 0 & 0 \\
0 & 14 & 0 & -33 & 0 & 49 & 0 & 20 \\
0 & 0 & -25 & 0 & 0 & 0 & 59 & 0 \\
0 & -12 & 0 & -5 & 0 & 24 & 0 & 58 \\
\end{bmatrix}$$  \hspace{1cm} (11)

Considering $H_{w,N}$ is built based upon 1 and -1, only additions and subtractions are required in the computation. In addition, as there are a number of zeros in $A_N$, the calculation burden increase is marginal. For larger TU sizes, i.e., $16 \times 16$ and $32 \times 32$, DCT transform is used. Since different transforms are utilized for various TU sizes, the generalized sum of absolute transformed difference $SATD_T$ is introduced in the following sections as the substitution for SATD where the subscript $T$ denotes the transform core.

### B. G-AZB Detection

For G-AZB, SAD and $SATD_T$ carry important information that can be used to as the summary for the TU characteristics. Here, we adopt a mathematical derivation based method, and we want to emphasize that our scheme is advantageous over the previous works such as [26] in several ways by utilizing more strict threshold. Firstly, we use more efficient transform by DCT-like matrix for $4 \times 4$ and $8 \times 8$ TU instead of using Hadamard transform. Secondly, more strict conditions are introduced in the mathematical derivation of the threshold.

In theory, all transform coefficients in the given TU should satisfy the constraint in Eq.7 if it is detected as G-AZB. Then we have:

$$\sum_{u=0}^{N-1} \sum_{v=0}^{N-1} |Z(u,v)| < \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} T_h(u,v),$$  \hspace{1cm} (12)

which can be further derived as follows,

$$SATD_T < \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} \left( \frac{2^{Q bits} - offset}{M_{QP/6}} \right) = N^2 \left( \frac{2^{Q bits} - offset}{M_{QP/6}} \right).$$  \hspace{1cm} (13)

Therefore, one threshold $\Gamma_1^{SATD_T}$ can be obtained as,

$$\Gamma_1^{SATD_T} = N^2 \left( \frac{2^{Q bits} - offset}{M_{QP/6}} \right).$$  \hspace{1cm} (14)

For the prediction residuals, the Laplacian distribution is used to model the residual data distribution, and then the corresponding relationship between residuals and transform coefficients can be derived. The Laplacian distribution is formulated as follows

$$p(x) = \frac{1}{2b} e^{-\frac{|x|}{b}},$$  \hspace{1cm} (15)

where $\sigma$ is the standard deviation of residual data $x$ and $b$ is the scale parameter. The expected value of $|x|$ can be deduced as:

$$E[|x|] = \int_{-\infty}^{+\infty} |x| \cdot \frac{1}{2b} e^{-\frac{|x|}{b}} dx = b,$$  \hspace{1cm} (16)

with,

$$b = \frac{\sigma}{\sqrt{2}}.$$  \hspace{1cm} (17)

Since

$$SAD = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} |x|,$$  \hspace{1cm} (18)

we can have the following relationship,

$$\sigma \approx \sqrt{2 \cdot \frac{SAD}{N^2}}.$$  \hspace{1cm} (19)

The variance of transform coefficients in $(u,v)^{th}$ position can be calculated according to [33], [34] as follows,

$$\sigma_{dct}^2(u,v) = \frac{\sigma^2}{N^2} \cdot u v,$$  \hspace{1cm} (20)

with,

$$uv = [AH_{w,CA}^TH_{w,CA}^T]_{u,u} [AH_{w,CA}^TH_{w,CA}^T]_{u,v},$$

where $[.]_{u,u}$ denotes the element in $(u,u)^{th}$ position and $C$ is the relevance metric,

$$C = \begin{bmatrix}
1 & \rho & \rho^2 & \ldots & \rho^{N-1} \\
\rho & 1 & \rho & \ldots & \rho^{N-2} \\
\rho^2 & \rho & 1 & \ldots & \rho^{N-3} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\rho^{N-1} & \rho^{N-2} & \rho^{N-3} & \ldots & 1
\end{bmatrix}.$$  \hspace{1cm} (21)

Here, $\rho$ is the correlation coefficient. In particular, larger $\rho$ value indicates that the input signal shares more homogenous visual content. Generally, $\rho$ is set to be 0.6 following published works [20], [22], [35], [36]. As such, the standard derivation in $(u,v)^{th}$ position can be obtained by combining Eq.(19) and Eq.(20):

$$\sigma_{dct}(u,v) = \frac{\sqrt{2}}{N} \cdot SAD \cdot \sqrt{uv}.$$  \hspace{1cm} (22)

It is has been proved that there is a linear relationship between SAD and $SATD_T$ [22], and then we have:

$$SAD = \kappa \cdot SATD_T,$$  \hspace{1cm} (23)

where $\kappa$ is defined as:

$$\kappa = \frac{1}{2N^2} \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} \sqrt{uv}.$$  \hspace{1cm} (24)
Thus, by substituting SAD in Eq.(22) with Eq.(23), \( \sigma_{dct}(u, v) \) can be represented as:

\[
\sigma_{dct}(u, v) = \frac{2^{\kappa}}{N^3} \cdot SATD_T \cdot \sqrt{uv}.
\]  

(25)

The \( \sigma_{dct}(u, v) \) denotes the standard deviation in the band \((u, v)\) and it can be used to characterize the transform coefficients based on the hypothesis that transformed coefficients obey Laplacian distribution [37]. According to the theory of probability, the probability of absolute of transform coefficient which is less than \( 3\sigma_{dct}(u, v) \) approximately accounts for 99.7\%. Therefore, it is reasonable to have,

\[
Z(u, v) \leq 3\sigma_{dct}(u, v)
\]  

(26)

and

\[
\max_{u,v \in [0,N-1]} (\sigma_{dct}(u, v)) < Th(u, v)/3.
\]  

(27)

By combining Eq.(25) and Eq.(27), we can have,

\[
SATD_T < \frac{N^3 \cdot Th(u, v)}{3 \sqrt{2\kappa} \max_{u,v \in [0,N-1]} (\sqrt{uv})}.
\]  

(28)

Therefore, the other threshold \( T_{SATD_T}^2 \) can be derived as,

\[
T_{SATD_T}^2 = \frac{N^3}{3 \sqrt{2\kappa}} \max_{u,v \in [0,N-1]} \left( \sqrt{uv} \right) \cdot \frac{2^{Q_{bits}} - offset}{M_Q P/6}.
\]  

(29)

Finally, the SAD and \( SATD_T \) based G-AZB detection threshold can be summarized as:

\[
SATD_T < \min_{u,v \in [0,N-1]} \left\{ T_{SATD_T}^1, T_{SATD_T}^2 \right\}.
\]  

(30)

C. P-AZB Detection

P-AZB detection is applied to detect the blocks which are quantized to AZBs via RDOQ. In other words, when only DZ+UTQ is applied, these blocks will not be quantized into AZBs. Therefore, P-AZB detection is performed right after G-AZB detection when the conditions in G-AZB detection are not satisfied.

Since accurate P-AZB detection method contributes significantly for the larger TU blocks, here we further investigate the scenario of P-AZB detection for larger TU sizes. In particular, the coefficient distributions for the larger TU, i.e., \( 16 \times 16 \), \( 32 \times 32 \), are explored in Fig. 3 with absolute quantized coefficient values being 1, 2 or larger than 2 for AZBs and non-AZBs. For the AZBs, the maximum coefficient amplitude tends to be smaller than 2 under different QPs. As such, the coefficient magnitude is an efficient clue to determine non-AZBs. Thus, the AZB detection can be performed based on searching transform coefficient amplitudes in the given TU. However, for large TUs, to avoid time-consuming operation traversing all coefficients, we propose a new method to detect the maximum transform coefficients based on the frequency band.

Before performing RDOQ, the temporal level termed as \( l(u, v) \) is pre-calculated based on DZ+UTQ irrespective of frame type. In RDOQ, there are several candidate levels for each \( l(u, v) \), and the optimal one among these candidates is determined by RDO. Table I lists the available candidates for each \( l(u, v) \). In particular, for the case of \( l(u, v) \) being 0, the final quantized coefficient will be definitely zero even without RDOQ. However, only \( l(u, v) \) being 1 or 2 is able to be adjusted to 0, which means if the given TU is AZB after RDOQ, the prerequisite is that the \( l(u, v) \) of all coefficients need to be within 2. Fig. 4 to Fig. 7 illustrate the \( l(u, v) \) distributions with different QPs for each TU layer in these P-AZB TUs. We can observe that all the non-zero \( l(u, v) \) are not larger than 2. The statistical results suggest that only all the \( l(u, v) \) are within the range \([0, 2]\), the TU can be encoded as P-AZB. This motivates us to search for the largest coefficient in the TU for the identification of P-AZB.

To reduce the coefficients searching burden, we divide each TU into two parts: low frequency part and high frequency part. In essence, the boundary for low and high frequency parts balances the searching complexity and detection accuracy. For high bit rate coding, more non-zero \( l(u, v) \) are generated, such that our detection area should be larger than that in the...
low bit rate scenario. Therefore, the boundary should be adaptive to the QP values. Here, we proposed a deterministic scheme for the identification of the block for the low frequency part, which locates in the top left corner of TU, as shown in Fig. 8,

$$B_{LF} = \max_{QF \in \{0, \ldots, \max QP\}} \left\{ \text{round} \left( \left( 1 - \frac{QP}{\max QP} \right) \cdot N \right), 1 \right\},$$  \hspace{1cm} (31)

where $B_{LF}$ is the block size of low frequency part. $\max QP$ denotes the maximum QP setting in HEVC and $QP$ is the quantization parameter for current TU.

Considering the fact that only the $l(u, v)$ of 1 or 2 in TU can be further quantized to zero, and moreover large amplitude coefficients always concentrate in the low frequency part, we only focus on the low frequency part and guarantee the maximum absolute $l(u, v)$ within it to be smaller than 2. To reduce computational cost of DZ+UTQ, we construct our detection threshold based on the transform coefficients instead of $l(u, v)$, and thus we have,

$$\max_{u, v \in [0, B_{LF}]} \{|Z(u, v)|\} \geq \frac{(\text{MUL} + \epsilon) \cdot 2^{Q_{\text{bits}}} - \text{offset}}{M_{QP/6}},$$  \hspace{1cm} (32)

Fig. 4. The examples of $l(u, v)$ distribution map in the $4 \times 4$ P-AZB. (a) BasketballPass QP = 22. (b) BasketballPass QP = 32. (c) BasketballPass QP = 42. (d) Cactus QP = 22. (e) Cactus QP = 32. (f) Cactus QP = 42.

Fig. 5. The examples of $l(u, v)$ distribution map in the $8 \times 8$ P-AZB. (a) BasketballPass QP = 22. (b) BasketballPass QP = 32. (c) BasketballPass QP = 42. (d) Cactus QP = 22. (e) Cactus QP = 32. (f) Cactus QP = 42.

Fig. 6. The examples of $l(u, v)$ distribution map in the $16 \times 16$ P-AZB. (a) BasketballPass QP = 22. (b) BasketballPass QP = 32. (c) BasketballPass QP = 42. (d) Cactus QP = 22. (e) Cactus QP = 32. (f) Cactus QP = 42.

Fig. 7. The examples of $l(u, v)$ distribution map in the $32 \times 32$ P-AZB. (a) BasketballPass QP = 22. (b) BasketballPass QP = 32. (c) BasketballPass QP = 42. (d) Cactus QP = 22. (e) Cactus QP = 32. (f) Cactus QP = 42.

Fig. 8. Illustration of the low and high frequency partitions.
Fig. 9. The relationship between RD Cost and SAD in 16 × 16 and 32 × 32 AZB TUs for BasketballPass. (a) 4 × 4 QP = 22. (b) 4 × 4 QP = 32. (c) 4 × 4 QP = 42. (d) 8 × 8 QP = 22. (e) 8 × 8 QP = 32. (f) 8 × 8 QP = 42. (g) 16 × 16 QP = 22. (h) 16 × 16 QP = 32. (i) 16 × 16 QP = 42. (j) 32 × 32 QP = 22. (k) 32 × 32 QP = 32. (l) 32 × 32 QP = 42.

Fig. 10. The relationship between the number of non-zero transform coefficients nonZeroNum and SATD T in 16 × 16 and 32 × 32 AZB TU for BasketballPass. (a) 16 × 16 QP = 12. (b) 16 × 16 QP = 22. (c) 16 × 16 QP = 32. (d) 16 × 16 QP = 42. (e) 32 × 32 QP = 12. (f) 32 × 32 QP = 22. (g) 32 × 32 QP = 32. (h) 32 × 32 QP = 42.

where MUL denotes the maximum \( l(u, v) \) and \( \epsilon \) is the compensating factor. In this method, we set \( MUL = 2 \) and \( \epsilon = 0.2 \), respectively.

In addition, to further detect the AZBs which are generated by the RDOQ, we design the RDO-based threshold by comparing the RD costs of a TU when it is detected as AZB and non-AZB. In particular, the RD costs can be calculated by:

\[
RDCost_{AZB} = SSD_{AZB} + \lambda \times R_{AZB},
\]

\[
RDCost_{non-AZB} = SSD_{non-AZB} + \lambda \times R_{non-AZB},
\]

(33)

where \( SSD_{\ast} \) and \( R_{\ast} \) denote the distortion and entropy bits, respectively. In particular, the \( R_{AZB} \) can be approximated to 1 since there is no coefficients needed to encode and only one bit flag is required for signal, as described in [1]. Therefore, we can have,

\[
RDCost_{AZB} = SSD_{AZB} + \lambda.
\]

(34)

Here, the \( SSD_{AZB} \) is calculated by:

\[
SSD_{AZB} = ||r - rr|| = ||r||^2,
\]

(35)

where \( r \) and \( rr \) are the original and reconstructed residual data vector, respectively. For TUs including only zero coefficients after RDOQ, the \( rr \) is zero vector as well. As such, the \( RDCost_{AZB} \) in Eq.(34) can be written as,

\[
RDCost_{AZB} = ||r||^2 + \lambda.
\]

(36)
Moreover, as the residual data for inter prediction will be mostly 1 and 0, we can have,
\[
\text{RDCost}_{AZB} = r_0^n + \cdots + r_{N^2-1}^2 + \lambda \approx |r_0| + \cdots + |r_{N^2-1}| + \lambda = \text{SAD}^2 + \lambda. \tag{37}
\]

The relationship between RD cost and SAD is shown in Fig. 9, where we can see that approximation of the RD cost with Eq.(37) is practical. To unify the RD cost at pixel level, we modify Eq.(37) by a constant \(c\), which is a function of TU size \(N\),
\[
\text{RDCost}_{AZB} = (\text{SAD}^2 + \lambda)/c. \tag{38}
\]

Here, \(c\) is set to be 17, 37, 148 and 580 which are the same as in [24] and [26] for 4\(\times\)4, 8\(\times\)8, 16\(\times\)16 and 32\(\times\)32 TUs, respectively. Combining Eq.(38) with Eq.(23), we can have,
\[
\text{RDCost}_{AZB} = (\kappa^2 \cdot \text{SATD}_T^2 + \lambda)/c. \tag{39}
\]

where the \(\kappa\) is obtained from the G-AZB detection.

For the RD cost of non-AZB, both \(\text{SSD}_{non-AZB}\) and \(\text{R}_{non-AZB}\) are derived. Assuming that the distortion \(\text{SSD}_{non-AZB}\) can be obtained in the transform domain by original and reconstructed quantized coefficient matrices, we can have
\[
\text{SSD}_{non-AZB} = s^2 \cdot Q_{\text{step}}^2 \cdot \sum_{i=0}^{N^2-1} (C_i - \tilde{C}_i)^2, \tag{40}
\]

Fig. 11. Sensitivity of \(c\) regarding on the average Detection Rate of Traffic and ParkScene under RA. (a) FNR. (b) FPR.

where \(s\) is the scaling factor and \(C_i\) and \(\tilde{C}_i\) are denoted as the \(i\)-th quantized and reconstructed quantized coefficient matrices.

The quantized error \(|C_i - \tilde{C}_i|\) for \(i\)-th quantized coefficient tends to be small after RDOQ, such that we set a threshold value \(\text{Th}_c\), which covers about 95.5% of \(|C_i - \tilde{C}_i|^2\) by learning from video sequences BasketballPss, Cactus with 100 frames,
\[
|C_i - \tilde{C}_i|^2 < \text{Th}_c. \tag{41}
\]

The QP-based threshold value \(\text{Th}_c\) for each TU size can be summarized in Table II. By combining Eq.(40) and Eq.(41), we can have,
\[
\text{SSD}_{non-AZB} = s^2 \cdot Q_{\text{step}}^2 \cdot \sum_{i=0}^{N^2-1} \text{Th}_c \tag{42}
\]

For \(\text{R}_{non-AZB}\), a rate estimation model is employed based on the transform coefficients as that in [38] and [39],
\[
\text{R}_{non-AZB} = \alpha \cdot \text{SATD}_T + \beta \cdot \text{nonZeroNum} + \gamma, \tag{43}
\]

with,
\[
\text{nonZeroNum} = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} I(Z(u, v))
\]
and

$$I(Z(u,v)) = \begin{cases} 1, & \text{if } Z(u,v) = 0 \\ 0, & \text{otherwise,} \end{cases}$$

where the parameters $\alpha$ and $\beta$ are obtained based on offline training, as shown in Table III and Table IV. The training scheme and method have been proposed in our previous work in [38]. $\gamma$ is set as 0 since the TU will be skipped once all the transform coefficients are zero. Moreover, the relationship between nonZeroNum and SATD_T can be well fitted by piecewise linear function based on the statistical results in Fig. 10, and $Th_{SA T D_T}$ is used to classify two parts of linear curve. $\phi$ is the slope between nonZeroNum and SATD_T. Thus the $R_{non-AZB}$ is modified as:

$$R_{non-AZB} = \alpha \cdot SATD_T + \beta \cdot \frac{N^2}{2}, \text{if } SATD_T > Th_{SA T D_T}$$

(44)

In particular, for $4 \times 4$ and $8 \times 8$ TU, the $Th_{SA T D_T}$ is approaching to zero, i.e., nonZeroNum = $N^2$. Then we have:

$$R_{non-AZB} = \alpha \cdot SATD_T + \beta \cdot N^2$$

(45)

If the current TU is P-AZB, we can have the following relationship,

$$RDCost_{AZB} < RDCost_{non-AZB}.$$  

(46)

Combining Eq.(33), Eq.(39), Eq.(42), and Eq.(44) with the case $SATD_T > Th_{SATD_T}$, we can formulate Eq.(46) as:

$$(\kappa^2 \cdot SATD_T^2 + \lambda)/c < s^2 \cdot Q_{step}^2 \times \sum Th_e + \lambda \cdot (\alpha \cdot SATD_T + \beta \cdot N^2).$$

(47)

The larger solution of this quadratic equation is:

$$SATD_T^{right} = \frac{\alpha \cdot \lambda \cdot c}{2\kappa^2} + \frac{\sqrt{\alpha^2 \cdot \lambda^2 \cdot c^2 - 4AC}}{2\kappa^2}$$

(48)

with,

$$AC = \kappa^2 \cdot \left( \lambda - \beta \cdot \lambda \cdot c \cdot N^2 - s^2 \cdot Q_{step}^2 \cdot \sum Th_e \right).$$

Thus, we can get the left and right boundary of P-AZB as:

$$Th_{SATD_T} < SATD_T < \left[ SATD_T^{right} + \frac{1}{2} \right].$$

(49)

Similarly, for the case $SATD_T \leq Th_{SATD_T}$, the smaller solution of this quadratic equation is:

$$SATD_T^{left} = \frac{\lambda \cdot c \cdot (\alpha + \beta \cdot \phi) - SQRT}{2\kappa^2}$$

(50)

with,

$$SQRT = sqrt \left( \frac{\lambda^2 \cdot c^2 \cdot (\alpha + \beta \cdot \phi)^2 + 4\kappa^2 \cdot \left( s^2 \cdot Q_{step}^2 \cdot c \cdot Th_e - \lambda \right)}{4} \right).$$

(51)

Thus, the other limitation zone with left and right boundary can be described as:

$$\left[ SATD_T^{left} + \frac{1}{2} \right] < SATD_T \leq Th_{SATD_T}.$$  

(52)

Therefore, the final P-AZB detection can be transferred to detect whether the $SATD_T$ is located in the range formulated in Eq.(49) and Eq.(52).

### D. AZB Detection Algorithm

The proposed AZB detection scheme with G-AZB and P-AZB detection can be summarized in Algorithm 1:
TABLE VII

<table>
<thead>
<tr>
<th>Sequence</th>
<th>RA</th>
<th>G-AZB</th>
<th>+ P-AZB</th>
<th>G-AZB</th>
<th>TS</th>
<th>LD</th>
<th>G-AZB</th>
<th>+ P-AZB</th>
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<td>4.67%</td>
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<td>24.16%</td>
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</table>

Algorithm 1 The Proposed AZB Detection Algorithm

Input: The residual data of the current TU.
Output: The current TU is AZB or Not.
1. if SATD$_{T}$ satisfies Eq.(30) then
2. isAZB equals to 1.
3. else if $\max_{QPC \in \{0, max,QP\}} \{Z(u,v)\}$ satisfies Eq.(32) then
4. isAZB equals to 0.
5. else if SATD$_{T}$ satisfies Eq.(49) or Eq.(52) then
6. isAZB equals to 1.
7. end if

IV. EXPERIMENTAL RESULTS

To validate the accuracy and efficiency of the scheme, we implement it in HEVC reference software HM 16.9. The performance of the proposed algorithm is evaluated based on test sequences in HEVC common test conditions [40] (Class A - Class F) under Random Access (RA) and Low Delay B (LD) main profile configurations with QPs being 22, 27, 32 and 37. In this work, before showing the algorithm performance, we evaluate the model parameters $c$ and $\rho$. And then the R-D performance and computational complexity of the proposed scheme are presented, followed by the comparisons with state-of-the-art methods in terms of R-D performance, computational complexity and detection accuracy.

A. Model Parameters Evaluation

In this section, we firstly evaluate the parameters sensitivity of $c$ in Eq.(38) and Eq. (39), and the correlation coefficient $\rho$ in Eq.(21). The parameter $c$ values for different TU sizes are derived from off-line training process by fitting the relationship between the RD cost and SAD for practical compressed video sequences, which is introduced in [24] and [26], and we use the same $c$ values with them. The sensitivity of $c$ regarding on the accuracy of AZB detection method has also been verified as shown in Fig.11. Table VI lists the explanations of the criterions which are used to describe the detection accuracy. When the $c$ value becomes larger, there is a slight decrease on FNR and increase on FPR, respectively, since $c$ value has an effect on the $RDCost_{AZB}$. Larger $c$ will reduce the $RDCost_{AZB}$ and make more non-AZB blocks be detected as AZB resulting in the FPR increase. Similarly, when $c$ value is smaller, there are many AZB blocks will be misclassified into non-AZB resulting in FNR increase.

The parameter $\rho$ denotes the correlation coefficient of adjacent two pixels. To explore the influence of the parameter $\rho$ on the coding performance, we have tested the transform coding gain $G_{TC}$ for different transform kernels with different $\rho$. The transform coding gain $G_{TC}$ is defined in [41] using the following formulations:

$$G_{TC} = \frac{1}{N} \sum_{i=1}^{N} \sigma_{y_i}^2 \left( \frac{1}{\Pi_{i=1}^{N} \sigma_{y_i}^2} \right)^{1/N}$$

with, $\sigma_{y_i}^2 = TCCT^T$.

where $T$ means the transform matrix and $C$ is the covariance matrix of input signal. Fig.12 shows the transform coding gain for three transform kernels at different parameter values of $\rho$, from which we can see that the transform core using
B. RD Performance and Time Saving Evaluation

Table VII shows the experimental results of the proposed scheme, where $T_{S_q}$ denotes the time saving of transform and quantization including the corresponding inverse transform and de-quantization, $T_{Anchor,q}$ and $T_{Proposed,q}$ represent time saving of anchor and proposed algorithm, respectively. Similarly, $T_S$ is the total encoding time saving with $T_{Anchor}$ and $T_{Proposed}$ being the encoding time of anchor and proposed method, respectively. In particular, $T_{S_q}$ and $T_S$ can be calculated by:

$$T_{S_q} = \frac{T_{Anchor,q} - T_{Proposed,q}}{T_{Anchor,q}} \times 100\%$$

$$T_S = \frac{T_{Anchor} - T_{Proposed}}{T_{Anchor}} \times 100\%$$

From Table VII, we can see that if only G-AZB detection method is used, only 4.67% to 5.21% time saving with about...
TABLE VIII

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</tr>
<tr>
<td>SlideShow</td>
<td>0.27</td>
<td>-0.30</td>
<td>17.66</td>
<td>35.94</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.43</td>
<td>0.35</td>
<td>21.65</td>
<td>0.36</td>
</tr>
</tbody>
</table>

0.03% - 0.05% BD-rate degradation is achieved, which is very limited to improve the coding efficiency, since the number of G-AZB accounts for a very small proportion, especially for larger TU size, i.e., 32×32, as shown in Fig. 2 (a)-(d). In addition, the proposed G-AZB detection method aims to find out all AZBs without RD consideration. If the G-AZB detection method fails to classify current block as AZB, this block will be checked by the following P-AZB detection method as well. Therefore, the P-AZB detection method is able to save up to 24.16% transform and quantization time with less than 0.06% BD-BR increase. The overall time saving TS are 4.01% and 5.18% for RA and LD configuration, respectively.

To further validate our scheme, we illustrate the performances of the state-of-the-art AZB detection methods proposed by Lee et al. [24] and Fan et al. [26], and the experimental results are shown in Table VIII. We can see that Lee et al.’s method achieves 34.25% run-time saving while leading to 0.43% RD performance degradation. For Fan et al.’s method, it obtains 21.65% - 24.85% time saving on average with up to 0.35% BDBR loss. In Fig.13, the RD curves of BasketballDrive and BQSquare have been illustrated for the proposed, Lee et al.’s and Fan et al.’s methods. From curves in Fig.13, we can see that the proposed method has achieved a comparative RD performance with anchor (HM16.9), while the results of Lee et al.’s and Fan et al.’s method are worse than the anchor. Furthermore, to evaluate the trade-off between RD performance and time saving, we introduce a metric BTR (BD-BR and Time saving Ratio) in Eq.(56) to verify the overall performance of AZB detection methods.

\[
BTR = \frac{BDBR}{1 + T S_q} \times 100\%.
\]

The constant 1 is utilized to make \(1 + T S_q\) positive. Obviously, the smaller the BTR is, the better the trade-off is. In Fig.14, our method shows the smallest BTR under each QP compared with Lee et al.’s and Fan et al.’s methods for the sequences BasketballDrive and BQSquare. Note that the BDBR is the result of four QPs (22, 27, 32 and 37), while \(T S_q\) in Fig.14 is for each QP. In addition, more time saving is achieved in the low bit-rate scenario compared with that of high bit-rate case for all three methods since more all zero blocks and non-zero blocks with only a few coefficients are generated when the QP is larger.

C. Detection Accuracy Evaluation

In this section, we verify the performance in terms of the detection rate and detection accuracy. The detection rates comparisons in terms of FNR and FPR are illustrated in Table IX, in which the average values of all sequences under QP values 22, 27, 32, and 37 for each class and each TU type. From the comparison results, we can see that the detection accuracy of the proposed method is up to 95.5% on average when detecting AZBs for 16×16 and 32×32 TUs. For the non-AZBs, only 5.8% to 6.5% non-AZBs have been misclassified by our method into AZBs. By contrast, the detection error for non-AZBs in [24] is only 5% on average, but that of AZBs reaches up to 34.1%. Moreover, the detection errors both for AZBs and non-AZBs in [26] are around 15%. To compare the detection accuracy in detail, the overall detection accuracies (DA) of different TU sizes for different QPs under RA configuration are illustrated in Fig.15. We can see that the overall detection accuracy is higher as QP becomes larger, because larger QP results in detecting less AZBs. Our method achieves the stable and higher overall detection accuracy compared

\[
\text{BTR} = \frac{BDBR}{1 + T S_q} \times 100\%.
\]
with Lee et al.’s and Fan et al.’s methods for different TU sizes. In Fig.15(a) and (c), Lee et al.’s method for 4×4 is quite comparable with our method, but for the larger TU sizes, e.g., 16×16 and 32×32, our detection algorithm is very superior to Lee et al.’s and Fan et al.’s methods as shown in Fig.15(b) and (d).

V. CONCLUSION

In this paper, an efficient AZB detection method with the consideration of SDQ is proposed, and the scenarios that may lead to zero coefficient blocks are adequately covered by the G-AZB followed by P-AZB detection. In particular, the P-AZB detection follows the design philosophy of RDOQ process, where maximum transform coefficient amplitude and RDO with adaptive rate-distortion estimations are employed. The experimental results show that the proposed detection method is able to efficiently reduce the transform and quantization time in the RDO procedure with ignorable R-D performance degradation. Moreover, the detection accuracy of proposed method is quite competitive compared with the state-of-the-art methods, especially for larger TU sizes, i.e., 16×16 and 32×32.

REFERENCES


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