Interview Rate Distortion Analysis-Based Coarse to Fine Bit Allocation Algorithm for 3-D Video Coding

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Abstract—In three dimensional video coding (3-DVC), it is reasonable to allocate bits for texture videos and depth maps differently as the characteristic of texture videos is different with that of depth maps. In order to improve the accuracy of bit allocation performance for 3-DVC, a more accurate distortion model for virtual view and rate models for texture videos and depth maps are proposed based on interview rate distortion analysis. Based on the proposed models, the bit allocation optimization problem is resolved by a coarse to fine strategy. The proposed bit allocation algorithm is implemented in the High Efficiency Video Coding-based 3-DVC platform version 6.0 (3-D-HTM 6.0). Experimental results demonstrate that the proposed distortion and rate models are accurate; meanwhile, the absolute difference (denoted as “rate inaccuracy”) between the actual coding bit rate ($R_{ABR}$) and the target coding bit rate ($R_{TBR}$) of the proposed method is only 2.67% on average; while the rate inaccuracy of the existing planar model-based method is 17.71%. Besides, there is an average 29.68% complexity increment when comparing with the planar model-based method.

I. INTRODUCTION

With the rapid growth of social media applications, video information is taking up more and more network bandwidth and terminal storage space. Compared with the traditional monoscopic videos, three dimensional (3D) videos (3DVs) are more appealing to audiences for its impressive visual experiences. However, the bandwidth/storage constrain of network/terminal become intensified. In order to reduce the huge data volume of 3DV, Joint Collaborative Team for 3DV (JCT-3V), established by Moving Pictures Experts Group (MPEG) of International Organization for Standardization (ISO) and Video Coding Experts Group (VCEG) of International Telecommunication Union (ITU), is developing 3DVC standards [1], [2] based on the High Efficiency Video Coding (HEVC) Standard [3].

The widely used 3DV format consists of two kinds of information, i.e. n-view texture videos and the corresponding n-view depth maps. In the current 3D video coding test model [4], n is set as 2 or 3 for reducing data volume as much as possible. When users want to enjoy more views (in the n-view range) which are not coded and transmitted, the display terminal will render a virtual view based on user specified view position. The process is named as virtual view synthesis which is based on Depth-Image Based Rendering (DIBR) [5] technique, as shown in Fig. 1.

From Fig. 1, it is observed that the two kinds of information of a 3DV system, i.e. texture videos and depth maps, are different. Texture videos are adopted to describe the image content of the scene; however, depth maps are utilized to present the transformed physical distance between camera centers and objects in the scene. Compared with texture videos, depth maps are sparser and smoother. Besides, depth maps are not for viewing, but only for virtual views rendering. Accordingly, the influences of depth maps and texture videos on the quality of a virtual views as well as the 3DV system should be different. Thus, for achieving high coding performance in a bandwidth/storage limited 3DV system, bit allocation between texture videos and depth maps becomes an important issue in 3DV system.

In [5], fixed ratio (5:1) bit allocation is used, but the quality of virtual views and the 3DV system are not guaranteed.
Daribo et al. [6] made use of the standard deviations of depth maps and texture videos for the allocation of bits. However, the influences of depth maps degradation on the quality of virtual views are not analyzed; it also could not guarantee the optimal quality in the virtual views. A full search algorithm was proposed in [7] to find the optimal encoding parameters, i.e. quantization parameters (QP), for texture videos and depth maps. However, the complexity is too high to be applied for many practical applications. A distortion estimation model for virtual views is proposed in [8]. Based on the estimated distortion, the bit allocation problem is also solved by a search algorithm and the complexity of this algorithm is still so high that it cannot be applied easily. In order to reduce the computation complexity, an analytical distortion model was proposed for virtual views in our previous work [9]. Then, the bit allocation problem was formulated as a constrained optimization problem, and solved by using the Lagrangian multiplier method directly. Then, Han et al. [10] proposed an improved distortion model for virtual views, and use the total distortion of texture videos and virtual views as an objective function for the bit allocation optimization problem. In [11], a region-based view synthesis distortion estimation approach is investigated with respect to the distortion of texture videos and depth maps, and a corresponding bit allocation scheme is also designed. Besides, in [12], an asymmetric coding method of multi-view video plus depth (MVD) based 3D video is proposed on purpose of providing high-quality view rendering. In [13] and [14], during the bit allocation of texture videos and depth maps, inter-view bit allocations are considered and performed according to a predefined ratio. In [15], a scalable bit allocation method for 3DV streaming is proposed based on a varied rate constraint. In this paper, based on the coding structure of HEVC based 3DVC Test Platform, 3D-HTM [16], a coarse to fine bit allocation algorithms for 3DV is proposed based on inter-view rate distortion analysis so as to improve the accuracy of the bit allocation problem.

The remainder of the paper is organized as follows: In Section II, inter-view rate distortion analysis is performed so as to derive an exact distortion model for virtual views and rate models for both texture videos and depth maps. Based on the models, a coarse to fine bit allocation algorithms for 3DV is proposed in Section III. Experiments and conclusions are presented in Sections IV and V respectively.

II. INTERVIEW RATE DISTORTION ANALYSIS

The inter-view bit allocation problem of 3DVs can be regarded as an optimization problem, i.e. to achieve the minimum distortion of virtual view under a certain bit rate constraint. Once the optimization problem is solved, an optimal set of encoder parameters will be determined for 3DVs. In a 3DV encoder, inter-view prediction [17], [18] has been adopted as an important and effective coding tool. Therefore, it is necessary to derive a more precise rate and distortion model for 3DVC based on the inter-view dependency relationship. Currently, the test platform 3D-HTM contains 3 different QPs to control the output bit rates, i.e. QP of base view (BV) texture video (QP_t), QP of BV depth map (QP_d), and the QP difference (\( \Delta QP \)) between BV and non-base view (NBV). Therefore, QP_t (the corresponding quantization step, \( Q_t \)), QP_d (the corresponding quantization step, \( Q_d \)), and \( \Delta QP \) should be considered in the rate and distortion analysis.

A. Distortion Analysis

During the analysis, the mean squared error (MSE) between the original image and the corresponding reconstructed image is used as distortion criterion, which could be calculated as,

\[
D = \frac{1}{W \times H} \sum_{i=1}^{W} \sum_{j=1}^{H} [I(i,j) - I'(i,j)]^2, \tag{1}
\]

where \( W \) and \( H \) are the width and height of the image, \( I(i,j) \) and \( I'(i,j) \) are the original image and the reconstructed image respectively. For the synthesized virtual view, \( I(i,j) \) represents the virtual view synthesized from uncompressed texture and depth images; while \( I'(i,j) \) represent the virtual view synthesized from those compressed texture and depth images.

For a 3DV encoder, there exists an inter-view propagation error caused by inter-view prediction, i.e. the quantization step of BV (\( Q_{t, bv} \)) could also affect the distortion of NBV (\( D_{t, nbv} \)), as shown in Fig. 2.

Therefore, the relationship between \( D_{t, bv} \) and \( D_{t, nbv} \) should also be studied in order to derive an accurate distortion model for virtual view. Let \( I_{nv}(i) \) denotes the \( i^{th} \) pixel value in the BV...
texture image, $I_{nv}(i)$ denotes the predicted pixel value, and $I_{nv,rec}(i)$ denotes the reconstructed value of the pixel, as shown in Fig. 3. Accordingly, $I_{nv}(j)$, $I_{nv, pred}(j)$, and $I_{nv,rec}(j)$ are used to represent the $j$th pixel in the base view and the $j$th pixel of BV, as shown in Fig. 4) value, its predicted pixel value, and its reconstructed pixel value in the NBV texture image.

Thus, the coding error of the pixel $i$ in the BV and that of the pixel $j$ in the NBV could be written as

$$e_{nv}(i) = I_{nv}(i) - I_{nv,rec}(i),$$  
(2)$$e_{nv}(j) = I_{nv}(j) - I_{nv,rec}(j).$$  
(3)

Taking the inter-view prediction into account, since the $j$th pixel in the base view and the $i$th pixel in the non-base view are the matching pixels; the pixel difference between them should be zero. Accordingly, during the inter-view prediction of the encoder, the $i$th pixel in the base view will be chosen to predict the $j$th pixel in the non-base view. Thus, $I_{nv, pred}(j)$ approximates to $I_{nv,rec}(i)$ because of the noise. As a result, $e_{nv}$ could also be written as

$$e_{nv}(j) = I_{nv}(j) - I_{nv,rec}(j)$$
$$= I_{nv}(j) - I_{nv, pred}(j) + I_{nv, pred}(j) - I_{nv,rec}(j)$$
$$\approx I_{nv}(j) - I_{nv,rec}(i) + I_{nv,rec}(i) - I_{nv,rec}(j)$$
$$= e_{nv}(j) + I_{nv,rec}(i) - I_{nv,rec}(j).$$  
(4)

Therefore, the mean squared error ($D_{nv}$) of all the pixels in the NBV texture image could be written as

$$D_{nv} = \sum_{j=1}^{N} e_{nv}(j)^2 \approx E \left[ e_{nv}(j)^2 \right]$$
$$= E \left[ \{e_{nv}(j) + I_{nv,rec}(i) - I_{nv,rec}(j)\}^2 \right]$$
$$= E \left[ e_{nv}^2 + E \left[ I_{nv,rec}(i) - I_{nv,rec}(j) \right]^2 \right]$$
$$+ 2 \cdot E \left[ e_{nv}\left[I_{nv,rec}(i) - I_{nv,rec}(j)\right] \right].$$  
(5)

where $E\{\}$ denotes the expectation value of a certain $e_{nv}(j)^2$, and because of the Law of Large Numbers [19], the average value of $e_{nv}(j)^2$ approximates to its expectation value.

Since $e_{nv}$ could be proved to be independent with $I_{nv,rec}(i)$-$I_{nv,rec}(j)$ (the proof is provide in Appendix I), (5) could be rewritten as

$$\text{avg} \{e_{nv}^2\} = E \left[ e_{nv}^2 \right] + E \left[ I_{nv,rec}(i) - I_{nv,rec}(j) \right]^2$$
$$= D_{nv} + f \left( Q_{tv}, Q_{tnv} \right),$$  
(6)

were $f(Q_{tv}, Q_{tnv}) = E\{[I_{nv,rec}(i)-I_{nv,rec}(j)]^2\}$ which could be expanded via Taylor Series [20], i.e.

$$f \left( Q_{tv}, Q_{tnv} \right)$$
$$= f(0,0) + \left( Q_{tv} \frac{\partial}{\partial Q_{tv}} + Q_{tnv} \frac{\partial}{\partial Q_{tnv}} \right) f(0,0)$$
$$+ \frac{1}{2!} \left( Q_{tv} \frac{\partial}{\partial Q_{tv}} + Q_{tnv} \frac{\partial}{\partial Q_{tnv}} \right)^2 f(0,0) + \cdots$$
$$\approx f(0,0) + \left( Q_{tv} \frac{\partial}{\partial Q_{tv}} + Q_{tnv} \frac{\partial}{\partial Q_{tnv}} \right) f(0,0)$$
$$= \mu Q_{tv} + v Q_{tnv} + c_0,$$  
(7)

where $c_0 = f(0,0)$, which represents the inherent discrepancy between the $j$th pixel in the BV and the $j$th pixel in NBV. $\mu$ and $v$ are the two parameters. The reason why $f(Q_{tv}, Q_{tnv})$ could be expanded via Taylor Series is proved in Appendix II. The accuracy of (6) is verified in Fig. 5, from which we can observe...
that the \( f(Q_{t, bv}, Q_{t, nbv}) \) or \( f(Q_{d, bv}, Q_{d, nbv}) \) varies linearly with \( Q_{t, bv} \) (or \( Q_{d, bv} \)) and \( Q_{t, nbv} \) (or \( Q_{d, nbv} \)). Besides, for the two sequences Balloons and Newspaper shown in Fig. 5, the squared correlation coefficient between \( f(Q_{t, bv}, Q_{t, nbv}) \) and \( Q_{t, bv} \) are 0.9379 and 0.9035 respectively; those between \( f(Q_{t, bv}, Q_{t, nbv}) \) and \( Q_{t, nbv} \) are 0.9467 and 0.9122 respectively; those between \( f(Q_{d, bv}, Q_{d, nbv}) \) and \( Q_{d, bv} \) are 0.9824 and 0.9784 respectively; those between \( f(Q_{d, bv}, Q_{d, nbv}) \) and \( Q_{d, nbv} \) are 0.9649 and 0.9742 respectively, i.e. (7) is accurate.

Because the relationship between \( D_{t, bv} \) and \( Q_{t, bv} \) could be represented as (8) [21],

\[
D_{t, bv} = \varphi_1 Q_{t, bv},
\]

\( D_{t, nbv} \) could be represented as

\[
D_{t, nbv} = D_{t, bv} + f(Q_{t, bv}, Q_{t, nbv})
= \varphi_1 Q_{t, bv} + \varphi_2 Q_{t, bv} + \varphi_3 Q_{t, nbv} + c_{0,t},
\]

(9)

where \( m_t, n_t, \) and \( c_{0,t} \) are model parameters. Since the relationship between \( Q_\) and \( Q_P \) could be represented as (10) [10] by fitting,

\[
Q \approx e^{r_1 Q_P + r_2},
\]

(10)

where \( r_1 = 0.11535, r_2 = -0.4593 \). Thus, the QP difference \( (\Delta Q_P) \) between \( Q_{P_{t, bv}} \) and \( Q_{P_{t, nbv}} \) could be derived as

\[
\Delta Q_P = Q_{P_{t, nbv}} - Q_{P_{t, bv}},
\]

(11)

by solving the following equations

\[
\begin{align*}
Q_{t, nbv} & \approx e^{r_1 Q_{P_{t, nbv}} + r_2}, \\
Q_{t, bv} & \approx e^{r_1 Q_{P_{t, bv}} + r_2}, \\
\Delta Q_P & = Q_{P_{t, nbv}} - Q_{P_{t, bv}}.
\end{align*}
\]

(12)

Because, \( e^{r_1 \Delta Q_P} \) could be expanded by power series, i.e.

\[
e^{r_1 \Delta Q_P} = 1 + (r_1 \Delta Q_P) + (r_1 \Delta Q_P)^2 / 2! + \cdots
\approx r_2 \cdot \Delta Q_P + r_1 \Delta Q_P + p_0,
\]

(13)

which is verified in Fig. 6, \( D_{t, nbv} \) could be further represented as

\[
D_{t, nbv} = m_t Q_{t, bv} + n_t Q_{t, nbv} + c_{0,t}
= m_t Q_{t, bv} + n_t Q_{t, bv} (r_2 \Delta Q_P + r_1 \Delta Q_P + p_0) + c_{0,t}
= (n_t r_2 \Delta Q_P + n_t r_1 \Delta Q_P + m_t + n_t p_0) Q_{t, bv} + c_{0,t},
\]

(14)

which means that there exists a linear relationship between \( D_{t, nbv} \) and \( Q_{t, bv} \), and the slope between \( D_{t, nbv} \) and \( Q_{t, bv} \) depends on \( \Delta Q_P \). Similarly, \( D_{t, nbv} \) could also be derived as,

\[
D_{d, nbv} = n_d p_2 \Delta Q_P + n_d p_1 \Delta Q_P + n_d + n_d p_0 Q_{d, bv} + c_{0,d}.
\]

(15)

Consequently, by taking the planar model [9] into consideration, a more precise distortion model of virtual view could be written as,

\[
D_v = A (D_{t, bv} + D_{t, nbv}) + B (D_{d, bv} + D_{d, nbv})
= A (n_t p_2 \Delta Q_P + n_t p_1 \Delta Q_P + m_t + n_t p_0 + \varphi_t) Q_{t, bv}
+ B (n_d p_2 \Delta Q_P + n_d p_1 \Delta Q_P + m_d + n_d p_0 + \varphi_d) Q_{d, bv}
+ (A c_{0,t} + A c_{0,d}).
\]

(16)

For simplification, (16) is rewritten as

\[
D_v = (g_2 \Delta Q_P + g_1 \Delta Q_P + g_0) Q_{t, bv}
+ (h_2 \Delta Q_P + h_1 \Delta Q_P + h_0) Q_{d, bv} + C,
\]

(17)

where \( g_2, g_1, g_0, h_2, h_1, h_0, \) and \( C \) are the model parameters.

B. Rate Analysis

In a 3DV encoder, the output bits are composed of four parts, i.e. the coding bits of BV texture videos, NBV texture videos, BV depth maps, and NBV depth maps. For each part, the coding bit rate model could be represented as (18) [22],

\[
R = aQ^{-1},
\]

(18)

where \( a \) is a model parameter, \( Q \) is the quantization step. Therefore, take texture video as an example, the coding bit rate of BV and NBV texture video could be written as

\[
R_t = R_{t, bv} + R_{t, nbv} = \alpha_{t, bv} Q_{t, bv}^{-1} + \alpha_{t, nbv} Q_{t, nbv}^{-1}
= \alpha_{t, bv} Q_{t, bv}^{-1} + \alpha_{t, nbv} e^{-r_1 \Delta Q_P} Q_{t, bv}^{-1}.
\]

(19)

Since \( e^{r_1 \Delta Q_P} \) could also be expanded via power series, i.e.

\[
(e)^{r_1 \Delta Q_P} = 1 - (r_1 \Delta Q_P) + (r_1 \Delta Q_P)^2 / 2! + \cdots
= q_2 \cdot \Delta Q_P + q_1 \cdot \Delta Q_P + q_0,
\]

(20)

which is verified in Fig. 7, therefore, (19) could be further rewritten as

\[
R_t = \alpha_{t, bv} Q_{t, bv}^{-1} + \alpha_{t, nbv} e^{-r_1 \Delta Q_P} Q_{t, bv}^{-1}
= \alpha_{t, bv} Q_{t, bv}^{-1} + \alpha_{t, nbv} (q_2 \Delta Q_P + q_1 \Delta Q_P + q_0) Q_{t, bv}^{-1}
= (\alpha_{t, nbv} q_2 \Delta Q_P + \alpha_{t, nbv} q_1 \Delta Q_P + \alpha_{t, bv} q_0 + \alpha_{t, bv} Q_{t, bv}^{-1}).
\]

(21)

Similarly, the coding bit rate of depth maps could be represented as

\[
R_d = \left(\alpha_{d, nbv} q_2 \Delta Q_P + \alpha_{d, nbv} q_1 \Delta Q_P + \alpha_{d, bv} Q_{d, bv}^{-1}\right).
\]

(22)
Fig. 7. Relationship between $e^{-t_1^* \Delta QP}$ and $\Delta QP$, where $t_1 = 0.11535$.

Thereby, the total target bit rate could be represented as

$$R_{TBR} = R_t + R_d$$
$$= \left( \alpha_{t,nbv} q_2 \Delta^2_{QP} + \alpha_{t,bv} q_1 \Delta QP \right) + \left( \alpha_{d,nbv} q_2 \Delta^2_{QP} + \alpha_{d,bv} q_1 \Delta QP \right) + \left( \alpha_{d,nbv} q_0 + \alpha_{d,bv} \right) Q_{t,bv}^{-1} \beta \Delta_{QP} + \beta_0 \right) Q_{d,bv}^{-1}. \tag{23}$$

For easy representation, (23) could be rewritten as

$$R_{TBR} = \left( \alpha_2 \Delta^2_{QP} + \alpha_1 \Delta QP + \alpha_0 \right) Q_{t,bv}^{-1} + \left( \beta_2 \Delta^2_{QP} + \beta_1 \Delta QP + \beta_0 \right) Q_{d,bv}^{-1}. \tag{24}$$

III. PROPOSED COARSE TO FINE BIT ALLOCATION ALGORITHM

Based on the distortion and rate analysis in Section II, the 3DV bit allocation problem could be resolved by solving the optimization problem

$$\min \left( g_2 \Delta^2_{QP} + g_1 \Delta QP + g_0 \right) Q_{t,bv}$$
$$+ \left( h_2 \Delta^2_{QP} + h_1 \Delta QP + h_0 \right) Q_{d,bv} + C,$$

s.t. \( \left( \alpha_2 \Delta^2_{QP} + \alpha_1 \Delta QP + \alpha_0 \right) Q_{t,bv}^{-1} + \left( \beta_2 \Delta^2_{QP} + \beta_1 \Delta QP + \beta_0 \right) Q_{d,bv}^{-1} = R_{TBR}. \tag{25}$$

where $R_{TBR}$ represents the target bit rate. However, both the objective and the constraint function of (25) are not convex, which makes the solving procedure difficult. Therefore, in this work, $\Delta QP$ is used to fine tune the 3D video bit allocation procedure so as to meet the target bit rate requirements. Firstly, we can set a default $\Delta QP$ value (denoted as $\Delta QP_1$) to calculate $Q_t$ and $Q_d$ using the method in [9]. Then in the second step, we calculate the optimal $\Delta QP$ (denoted as $\Delta QP_2$) under the given $Q_t$ (the corresponding $QP$ is $QP_1$) and $Q_d$ (the corresponding $QP$ is $QP_d$) to make the $R_{ABR}$ close to the $R_{TBR}$.

Based on (21) and (22), for a 3DV sequence, when the quantization steps $Q_t$ and $Q_d$ are confirmed, the distortion and rate model could be rewritten as

$$D_v = G_2 \cdot \Delta^2_{QP} + G_1 \cdot \Delta QP + G_0.$$
$$R_{TBR} = K_2 \cdot \Delta^2_{QP} + K_1 \cdot \Delta QP + K_0. \tag{26}$$

where, $G_2, G_1, G_0, K_2, K_1, K_0$ are six parameters that depends on $Q_t$ and $Q_d$, and they can be calculated by pre-code the NBV texture video and depth maps under the given $Q_t$ and $Q_d$. Then, the bit allocation problem could be represented as (28),

$$\min \left( G_2 \cdot \Delta^2_{QP} + G_1 \cdot \Delta QP + G_0 \right)$$
$$s.t. \quad K_2 \cdot \Delta^2_{QP} + K_1 \cdot \Delta QP + K_0 = R_{TBR}. \tag{28}$$

By solving the quadratically constrained quadratic program (QCQP) [23] problem in (28), the optimal $\Delta QP$ (denoted as $\Delta QP_2$) could be written as

$$\Delta QP_2 = \frac{-\left( -K_1 - \sqrt{K_1^2 - 4K_2 (K_0 - R_{TBR})} \right) / (2K_2)}{\begin{cases} \text{if } K_2^2 - 4K_2 (K_0 - R_{TBR}) \geq 0 \\ -K_1 / (2K_2) \text{ else} \end{cases}} \tag{29}$$

Since $R_{ABR,1}$ could be represented as

$$R_{ABR,1} = K_2 \cdot \Delta^2_{QP_1} + K_1 \cdot \Delta QP_1 + K_0, \tag{30}$$

Subsequently,

$$\Delta QP_2 - \Delta QP_1 = \frac{\sqrt{K_1^2 - 4K_2 (K_0 - R_{TBR})} - \sqrt{K_1^2 - 4K_2 (K_0 - R_{TBR})}}{2K_2}. \tag{31}$$

From (31), we can conclude that when $R_{ABR,1}$ is larger than $R_{TBR}$, $\Delta QP$ should be increased ($\Delta QP_2 > \Delta QP_1$); and when the $R_{ABR,1}$ is smaller than $R_{TBR}$, $\Delta QP$ should be decreased ($\Delta QP_2 < \Delta QP_1$). In summary, the proposed coarse to fine bit allocation strategy could be described as the following,

Step 1: Set Target Bit Rate ($R_{TBR}$);
Step 2: Set Initial $\Delta QP = \Delta QP_1$ (a default value);
Step 3: Calculate $Q_t$ and $Q_d$ by using the method in [9];
Step 4: Calculate model parameters $K_2, K_1, \text{ and } K_0$ by pre-coding NBV texture video and depth maps for two times with different $\Delta QP$ (specially, $\Delta QP$) respectively.
Step 5: Calculate $\Delta QP_2$ by using (29);
Step 6: Encode the video sequences with $Q_t, Q_d, \text{ and } \Delta QP_2$.

IV. EXPERIMENTAL RESULTS

In the experiments, we first check the accuracy of the proposed distortion model and rate models. Then, the performance of the proposed coarse to fine bit allocation algorithm is verified. Six 3DV sequences [24] which are adopted by JCT-3V, i.e., Balloons (view 3 is encoded as BV, view 1 is encoded as NBV), BookArrival (view 8 is encoded as BV, view 10 is encoded as NBV), Kendo (view 3 is encoded as BV, view 1 is encoded as NBV), Newspaper (view 4 is encoded as BV, view 2 is encoded as NBV), GhostTownFly (view 5 is encoded as BV, view 9 is encoded as NBV), and UndoDancer (view 5 is encoded as BV, view 1 is encoded as NBV), are used in the experiments. The 3DVC platform, 3D-HTM version 5.0 [16] is employed to encode those sequences, while the rendering software [16] integrated in 3D-HTM is used to synthesize virtual views. The encoder configuration files are set as the same with that of common test condition [25] of 3D-HTM.
A. Distortion Model Verification

In this part, the accuracy of the distortion model shown in (17) is verified. However, (17) is a model with 3 parameters, which means that it cannot be shown by figures easily. From the derivation of (17), we can observe that (17) is obtained by adding (14) with (15). Therefore, we could verify (14) and (15) so as to validate the accuracy of (17).

From (14), we can observe that there is a quadratic relationship between \( D_t, nbv \) and \( \Delta QP \), and a linear relationship between \( D_t, nbv \) and \( \Delta QP \). Fig. 8 shows the relationship among \( D_t, nbv, Q_t, bv \), and \( \Delta QP \). Besides, the squared correlation coefficients \( r^2 \) between the actual \( D_t, nbv \) and the fitted values are shown in Table I. From the table, we can observe that the \( r^2 \) are all larger than 0.96, which implies that (14) is accurate. Similarly, from (15), it can be observed that there is a quadratic relationship between \( D_d, nbv \) and \( \Delta QP \), and a linear relationship between \( D_d, nbv \) and \( Q_d, bv \), as shown in Fig. 9. Moreover, Table II, the \( r^2 \) for all the different video sequences are also larger than 0.99, i.e. (15) is accurate.

Besides, the accuracy of the proposed model in (17) is also compared with the planar model in [9]. The squared correlation coefficients (denoted as \( r_1^2 \)) and the root of mean squared error (RMSE) between the actual \( D_t \) and the one fitted from (17) and those (denoted as \( r_2^2 \) and RMSE) between the actual \( D_t \) and the one fitted from the planar model in [9] are shown in Table III, from which we can observe that \( r_1^2 \) is larger than \( r_2^2 \), while RMSE is smaller than RMSE. Thus, it implies that the proposed model is more accurate than the planar model in [9].

B. Rate Model Verification

In this part, in order to verify the accuracy of the rate model shown in (24) which could not be shown as figures easily, the rate models (21) and (22) are verified. From (21), when \( \Delta QP \) is confirmed, there will be a linear relationship between \( R_t \) and \( Q_t, bv^{-1} \); when \( Q_t, bv \) is confirmed, there will be a quadratic relationship between \( R_t \) and \( \Delta QP \). The relationship among \( R_t, Q_t, bv^{-1} \), and \( \Delta QP \) is shown in Fig. 10 and Table IV.

Similarly, the relationship among \( R_d, Q_d, bv^{-1} \), and \( \Delta QP \) is shown in Fig. 11 and Table V. From Tables IV and V, we can observe that the \( r^2 \) between the actual \( R_t \) and the value fitted by (21) are all larger than 0.88, and the \( r^2 \) between the actual \( R_d \) and the value fitted by (22) are all larger than 0.94,
Fig. 9. Relationship between $D_{d,bv}$ and $\Delta_{QP}$, each line corresponds to a fixed $Q_{d,bv}$. (a) Balloons. (b) BookArrival. (c) Kendo. (d) Newspapercc. (e) GhostTownFly. (f) UndoDancer.

Fig. 10. Relationship among $R_{t,bv}$, $Q_{t,bv}$, and $\Delta_{QP}$. (a) Balloons. (b) BookArrival. (c) Kendo. (d) Newspapercc. (e) GhostTownFly. (f) UndoDancer.

TABLE IV
SQUARED CORRELATION COEFFICIENTS ($r^2$) BETWEEN THE ACTUAL $R_{t,bv}$ AND THE VALUES FITTED BY (21)

<table>
<thead>
<tr>
<th>Sequences</th>
<th>$r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balloons</td>
<td>0.9756</td>
</tr>
<tr>
<td>BookArrival</td>
<td>0.8829</td>
</tr>
<tr>
<td>Kendo</td>
<td>0.9781</td>
</tr>
</tbody>
</table>

TABLE V
SQUARED CORRELATION COEFFICIENTS ($r^2$) BETWEEN THE ACTUAL $R_{d,bv}$ AND THE VALUES FITTED BY (22)

<table>
<thead>
<tr>
<th>Sequences</th>
<th>$r^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balloons</td>
<td>0.9877</td>
</tr>
<tr>
<td>BookArrival</td>
<td>0.9949</td>
</tr>
<tr>
<td>Kendo</td>
<td>0.9940</td>
</tr>
</tbody>
</table>

which mean that (21) and (22) are accurate. Therefore, the rate model shown in (24) is accurate.

C. Bit Allocation Performance Comparison

In this part, the Planar Model Based Method in [9] is used as a reference to evaluate the performance of the proposed algorithm (denoted as “Proposed Method”). For the sequences Balloons, BookArrival, Kendo, and Newspapercc, the target coding bit rates are set as 1024kbps, 768kbps, 512kbps, and 384kbps; while for the sequences GhostTownFly and UndoDancer, the target coding bit rates are set as 3072kbps, 2048kbps, 1024kbps, and 512kbps.

In the experiments, $Q_{t,bv}$ and $Q_{d,bv}$ are first confirmed by pre-coding all the BV and NBV texture videos and depth
maps for two times. Then based on $Q_{t,bv}$ and $Q_{d,bv}$, NBV texture video and depth map are pre-coded for two times so as to confirm the $\Delta Q_{OP}$. Table VI shows the confirmed $Q_{t,bv}$, $Q_{d,bv}$ and $\Delta Q_{OP}$. Furthermore, the coding results based on those confirmed $Q_{t,bv}$, $Q_{d,bv}$, and $\Delta Q_{OP}$ values are shown in Table VII. From the table, we can observe that the absolute difference (denoted as “Rate inaccuracy”) between the actual coding bit rate ($R_{ABR}$) and the target coding bit rate ($R_{TBR}$) of the Proposed Method is only 2.67%, while that of the Planar Model Based Method is 17.71%, i.e. the Proposed Method is more accurate than the Planar Model Based Method.

Besides, the rate distortion performance of the Proposed Method and the Planar Model Based Method are also compared. The BD PSNR [26] and rate distortion curves are used to denote the rate distortion performance difference between the Proposed Method and the Planar Model Based Method. Since the proposed bit allocation algorithm is a coarse to fine solution of (25), the rate distortion performance of the proposed method is not the best. The $R_{ABR}$-PSNR performance of the Proposed Method and the Planar Model Based Method are shown in Fig. 12 and Table VII, from which we can observe that the rate distortion performance of the Proposed Method

TABLE VI
CONFIRMED $Q_{t,bv}$, $Q_{d,bv}$, AND $\Delta Q_{OP}$ OF THE PROPOSED METHOD AND THE PLANAR MODEL-BASED METHOD

<table>
<thead>
<tr>
<th>Sequences</th>
<th>$R_{ms}$ (kbps)</th>
<th>Planar Model Based Method</th>
<th>Proposed Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$Q_{t,bv}$</td>
<td>$Q_{d,bv}$</td>
<td>$Q_{d,bv}$</td>
</tr>
<tr>
<td>Balloons</td>
<td>1024</td>
<td>12.33</td>
<td>41.40</td>
</tr>
<tr>
<td>BookArrival</td>
<td>1024</td>
<td>8.25</td>
<td>29.29</td>
</tr>
<tr>
<td>Kendo</td>
<td>1024</td>
<td>14.06</td>
<td>66.14</td>
</tr>
<tr>
<td>Newspapercc</td>
<td>1024</td>
<td>15.01</td>
<td>33.29</td>
</tr>
<tr>
<td>GhostTownFly</td>
<td>1024</td>
<td>10.04</td>
<td>19.38</td>
</tr>
<tr>
<td>UndoDancer</td>
<td>1024</td>
<td>19.48</td>
<td>27.97</td>
</tr>
</tbody>
</table>
TABLE VII
BD PSNR BETWEEN THE PROPOSED METHOD AND THE PLANAR MODEL-BASED METHOD

<table>
<thead>
<tr>
<th>Sequences</th>
<th>Planar Model Based Method</th>
<th>Proposed Method</th>
<th>BD PSNR (dB) (Using RABR)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rate inaccuracy (%)</td>
<td>Virtual View PSNR (dB)</td>
<td>Rate inaccuracy (%)</td>
</tr>
<tr>
<td>Baloons</td>
<td>1024.00 883.03 13.77 40.89</td>
<td>1024.00 1048.52 2.39</td>
<td>1.29</td>
</tr>
<tr>
<td></td>
<td>768.00 684.38 10.89 40.18</td>
<td>768.00 758.61 1.22</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td>512.00 476.99 6.86 38.77</td>
<td>512.00 521.31 1.82</td>
<td>1.79</td>
</tr>
<tr>
<td></td>
<td>384.00 372.62 2.96 37.88</td>
<td>384.00 386.85 0.74</td>
<td>0.73</td>
</tr>
<tr>
<td>Kendo</td>
<td>1024.00 1134.62 10.80 41.56</td>
<td>1024.00 1134.62 1.80</td>
<td>1.79</td>
</tr>
<tr>
<td></td>
<td>768.00 642.53 16.34 40.44</td>
<td>768.00 788.09 2.62</td>
<td>2.51</td>
</tr>
<tr>
<td></td>
<td>512.00 408.52 20.21 39.20</td>
<td>512.00 524.69 2.48</td>
<td>2.46</td>
</tr>
<tr>
<td></td>
<td>384.00 314.36 18.14 38.47</td>
<td>384.00 376.23 2.02</td>
<td>2.01</td>
</tr>
<tr>
<td>BookArrival</td>
<td>1024.00 914.09 10.73 42.05</td>
<td>1024.00 1011.29 1.24</td>
<td>1.21</td>
</tr>
<tr>
<td></td>
<td>768.00 703.57 8.39 39.08</td>
<td>768.00 778.09 1.31</td>
<td>1.27</td>
</tr>
<tr>
<td></td>
<td>512.00 493.05 3.70 38.90</td>
<td>512.00 512.85 0.17</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>384.00 394.14 2.56 38.86</td>
<td>384.00 382.07 0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>Newspapercc</td>
<td>1024.00 894.76 12.62 38.25</td>
<td>1024.00 995.84 2.78</td>
<td>2.77</td>
</tr>
<tr>
<td></td>
<td>768.00 588.81 23.33 37.27</td>
<td>768.00 753.82 1.85</td>
<td>1.84</td>
</tr>
<tr>
<td></td>
<td>512.00 397.56 22.35 36.13</td>
<td>512.00 499.35 2.47</td>
<td>2.45</td>
</tr>
<tr>
<td></td>
<td>384.00 311.29 18.93 35.33</td>
<td>384.00 388.79 1.25</td>
<td>1.25</td>
</tr>
<tr>
<td>GhostTownFly</td>
<td>3072.00 2779.69 9.52 40.97</td>
<td>3072.00 3106.51 1.12</td>
<td>1.11</td>
</tr>
<tr>
<td></td>
<td>2048.00 1546.43 24.49 39.87</td>
<td>2048.00 2091.51 2.12</td>
<td>2.11</td>
</tr>
<tr>
<td></td>
<td>1024.00 674.98 34.08 38.15</td>
<td>1024.00 1005.65 1.79</td>
<td>1.80</td>
</tr>
<tr>
<td></td>
<td>512.00 344.64 32.69 36.33</td>
<td>512.00 477.46 6.75</td>
<td>6.74</td>
</tr>
<tr>
<td></td>
<td>384.00 311.29 18.93 35.33</td>
<td>384.00 388.79 1.25</td>
<td>1.25</td>
</tr>
<tr>
<td>UnderdoDancer</td>
<td>3072.00 2867.29 32.71 35.40</td>
<td>3072.00 3154.87 2.70</td>
<td>2.70</td>
</tr>
<tr>
<td></td>
<td>2048.00 1267.98 38.09 33.97</td>
<td>2048.00 2179.69 6.43</td>
<td>6.43</td>
</tr>
<tr>
<td></td>
<td>1024.00 674.76 34.11 32.21</td>
<td>1024.00 1095.73 7.01</td>
<td>7.00</td>
</tr>
<tr>
<td></td>
<td>512.00 426.12 16.77 30.94</td>
<td>512.00 509.87 0.42</td>
<td>0.42</td>
</tr>
<tr>
<td>Average</td>
<td>17.71</td>
<td>Average</td>
<td>2.67</td>
</tr>
</tbody>
</table>

Fig. 12. RABR-PSNR curves comparison between the proposed method and the planar model-based method in [9]. (a) Baloons. (b) BookArrival. (c) Kendo. (d) Newspapercc. (e) GhostTownFly. (f) UnderdoDancer.

is similar with that of the Planar Model Based Method for sequences Baloons, BookArrival, Kendo, and Newspapercc, and for sequences GhostTownFly and UnderdoDancer, the rate distortion performance of the Proposed Method is lower than that of the Planar Model Based Method. This is because that GhostTownFly and UnderdoDancer are generated from computer, while other sequences are captured from natural scenes, thus the rate distortion characteristics of the two video sequences are different from other sequences, i.e., a same bit rate increment may give lower virtual view quality increment compared with other sequences. As a result, the BD PSNRs of GhostTownFly and UnderdoDancer are much different from other sequences.

Since PSNR could not reflect the subjective quality effectively [27]–[30], we have given some subjective quality comparison as shown in Fig. 13. Since the proposed method
TABLE VIII

COMPLEXITY COMPARISON BETWEEN THE PROPOSED METHOD AND THE PLANAR MODEL-BASED METHOD

<table>
<thead>
<tr>
<th>Sequences</th>
<th>Planar Model Based Method</th>
<th>Proposed Method</th>
<th>Time Increasing(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time for pre-coding (s)</td>
<td>Time for encoding (s)</td>
<td>Total Time (s)</td>
</tr>
<tr>
<td>Balloons</td>
<td>1024</td>
<td>4144.82</td>
<td>2123.75</td>
</tr>
<tr>
<td></td>
<td>768</td>
<td>4144.82</td>
<td>1967.04</td>
</tr>
<tr>
<td></td>
<td>512</td>
<td>4144.82</td>
<td>1974.98</td>
</tr>
<tr>
<td></td>
<td>384</td>
<td>4144.82</td>
<td>2019.47</td>
</tr>
<tr>
<td>BookArrival</td>
<td>1024</td>
<td>3243.38</td>
<td>2107.06</td>
</tr>
<tr>
<td></td>
<td>768</td>
<td>3243.38</td>
<td>2111.54</td>
</tr>
<tr>
<td></td>
<td>512</td>
<td>3243.38</td>
<td>2080.17</td>
</tr>
<tr>
<td></td>
<td>384</td>
<td>3243.38</td>
<td>1926.00</td>
</tr>
<tr>
<td>Kendo</td>
<td>1024</td>
<td>4959.47</td>
<td>2810.85</td>
</tr>
<tr>
<td></td>
<td>768</td>
<td>4959.47</td>
<td>2356.20</td>
</tr>
<tr>
<td></td>
<td>512</td>
<td>4959.47</td>
<td>2392.00</td>
</tr>
<tr>
<td></td>
<td>384</td>
<td>4959.47</td>
<td>2206.58</td>
</tr>
<tr>
<td>Newspaperc</td>
<td>1024</td>
<td>2921.34</td>
<td>1932.74</td>
</tr>
<tr>
<td></td>
<td>768</td>
<td>2921.34</td>
<td>2086.68</td>
</tr>
<tr>
<td></td>
<td>512</td>
<td>2921.34</td>
<td>1858.34</td>
</tr>
<tr>
<td></td>
<td>384</td>
<td>2921.34</td>
<td>1783.91</td>
</tr>
<tr>
<td>GhostTownFly</td>
<td>1024</td>
<td>10842.15</td>
<td>7339.31</td>
</tr>
<tr>
<td></td>
<td>2048</td>
<td>10842.15</td>
<td>6074.45</td>
</tr>
<tr>
<td></td>
<td>512</td>
<td>10842.15</td>
<td>5652.48</td>
</tr>
<tr>
<td></td>
<td>1024</td>
<td>10842.15</td>
<td>6143.89</td>
</tr>
<tr>
<td>UndaDancer</td>
<td>1024</td>
<td>11166.46</td>
<td>4964.43</td>
</tr>
<tr>
<td></td>
<td>2048</td>
<td>11166.46</td>
<td>4824.53</td>
</tr>
<tr>
<td></td>
<td>512</td>
<td>11166.46</td>
<td>4755.70</td>
</tr>
<tr>
<td></td>
<td>384</td>
<td>11166.46</td>
<td>4558.09</td>
</tr>
</tbody>
</table>

Average 29.68

Fig. 13. Virtual view subjective quality comparison. Frame 24 of GhostTownFly by (a) planar model-based method [9] and (b) proposed method. Frame 24 of BookArrival by (c) planar model-based method [9] and (d) proposed method.

could utilize the given target bit rate effectively, from Fig. 13, it can be observed that the proposed method could give higher virtual view subjective quality than the planar model based method [9] at the same target bit rate.

D. Complexity Analysis

In the proposed method, model parameters should be calculated by pre-coding. For a certain 3D video sequence, we need first encode the texture videos (both the BV and the NBV) and depth maps (both the BV and the NBV) two times for determining $Q_{t,bv}$ and $Q_{d,bv}$ (the Planar Model Based Method could be completed at this step). Then, when the $Q_{t,bv}$ and $Q_{d,bv}$ are confirmed, the NBV texture video and depth map should be encoded for two times so as to confirm $\Delta Q$. Therefore, compared with the Planar Model Based Method, it is needed to additionally encode the NBV texture video and depth map for 2 times. Table VIII compares the encoding time of the Planar Model Based Method and the Proposed Method. From Table VIII, we can observe that compared with the Planar Model Based Method, an average 29.68% encoding time is increased by the Proposed Method.

V. CONCLUSION

In this paper, a coarse to fine bit allocation algorithm is proposed based on inter-view rate distortion analysis. Based on the analysis, a more accurate virtual view distortion model and rate model for texture videos and depth maps are proposed. Then, the 3DV bit allocation problem is converted as a constrained optimization problem, and solved by a coarse to fine strategy. Experimental results show that the proposed distortion and rate models are all accurate. Besides, the Rate inaccuracy of the Proposed Method is only 2.67%, while that of the Planar Model Based Method in [9] is 17.71%.

Moreover, the inter-view rate distortion analysis method could also be used in inter-frame rate distortion analysis so as to develop more accurate and efficient rate control algorithms for texture videos and depth maps, which is our future work.

APPENDIX I

Lemma 1: $e_{bv}$ is independent with $\tilde{I}_{bv}(i) - \tilde{I}_{nbv}(j)$.

Proof: Since the $i^{th}$ pixel in BV and the $j^{th}$ pixel in the NBV are two matching pixels, $I_{bv}(i)$ approximates to $I_{nbv}(j)$. Accordingly, when $I_{bv}(i)$ and $I_{nbv}(j)$ are encoded with the same encoder parameters (quantization
parameters, prediction modes, etc.), the reconstructed value $I_{bv, rec}(i)_{Q_{bv, P_{bv}}}$ is also close to $I_{bv, rec}(j)_{Q_{bv, P_{bv}}}$, where $l_{Q_{bv, P_{bv}}}$ represents the pixel is encoded with quantization step $Q_{bv}$ and prediction mode $P_{bv}$, i.e. $I_{bv, rec}(i)$ is the same with $I_{bv, rec}(j)_{Q_{bv, P_{bv}}}$. Similarly, $I_{bv, rec}(j)$ could be represented as $I_{bv, rec}(i)_{Q_{bv, P_{bv}}}$. Therefore, $I_{bv, rec}(i)-I_{bv, rec}(j)$ could be represented as

$$I_{bv, rec}(i)-I_{bv, rec}(j) = I_{bv, rec}(j)_{Q_{bv, P_{bv}}}-I_{bv, rec}(j)_{Q_{bv, P_{adv}}} = I_{bv, rec}(j)_{Q_{bv, P_{adv}}}-I_{bv, rec}(j)_{Q_{adv, P_{adv}}} = -e_{adv}()_{Q_{adv, P_{adv}}} + e_{adv}()_{Q_{adv, P_{adv}}},$$

where, $e_{adv}()_{Q_{adv, P_{adv}}} + e_{adv}()_{Q_{adv, P_{adv}}}$. Similarly, $I_{adv, rec}(j)$ could be written as $I_{adv, rec}(j)_{Q_{adv, P_{adv}}}$.

**APPENDIX II**

Based on the theory of Taylor Series, the constraint of equation (7) is that the function $f(Q_{adv}, P_{adv})$ should have partial derivatives at arbitrary orders.

To prove a function $f(x)$ is derivable, $F_1$ and $F_2$ (as shown in the following equations) must exist and equal.

$$F_1 = \lim_{\Delta x \to 0} \frac{f(x_0 + \Delta x, y_0) - f(x_0, y_0)}{\Delta x},$$

$$F_2 = \lim_{\Delta x \to 0} \frac{f(x_0, y_0) - f(x_0 + \Delta x, y_0)}{\Delta x}$$

Let $x$ denotes $Q_{adv}$, $y$ denotes $P_{adv}$. Therefore, for the function $f(Q_{adv}, P_{adv})$, $F_1$ could be written as,

$$F_1 = \lim_{\Delta x \to 0} \frac{f(x_0 + \Delta x, y_0) - f(x_0, y_0)}{\Delta x} = \frac{E}{\Delta x} \left \{ l_{adv, rec}(l_{adv, rec} - l_{adv, rec})^2 \right \}.$$ 

Since the $i$th pixel in the base view and the $j$th pixel in the non-base view are the matching pixels, theoretically speaking, the pixel difference between them should be zero. Accordingly, statistically speaking, during the inter-view prediction of the encoder, the $i$th pixel in the base view will be chosen to predict the $j$th pixel in the non-base view. Thus, $l_{adv, pred}(j)$ equals to $l_{adv, rec}(i)$. Accordingly, (34) could be written as,

$$F_1 = \lim_{\Delta x \to 0} \frac{E}{\Delta x} \left \{ l_{adv, rec}(l_{adv, rec} - l_{adv, rec})^2 \right \} - \frac{E}{\Delta x} \left \{ l_{adv, rec}(l_{adv, rec} - l_{adv, rec})^2 \right \} = 0,$$

where $e_{i0}$ is the coding noise depends on $Q_{adv}$.

Similarly, $F_2$ could also be proved to be zero. Furthermore, by using the same way, it could be proved that $f(Q_{adv}, P_{adv})$ have partial derivatives at arbitrary orders.

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