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ORIGINAL PAPER

Optimal I-frame assignment based on Nash bargaining solution in HEVC

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In most of video coding standards such as high efficiency video coding (HEVC), I-frame assignment is periodic even when the content change is minor, which degrades the coding efficiency. This paper proposes an I-frame assignment method based on Nash bargaining solution (NBS) in game theory to solve this problem. The encoded sequence is divided into several subsequences. Each subsequence is regarded as a game. All group of picture (GOP) in a subsequence is further divided into several sets of GOP. Each set of GOP is regarded as a player and compete for the number of I-frames. The optimal I-frame assignment is determined based on the generalized NBS. Experimental results show the proposed method outperforms HEVC by 5.21% bitrate saving.

Keywords: High efficiency video coding, Game theory, Nash bargaining solution, Intra-period, I-frame assignment

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I. INTRODUCTION

With the development of display technology and increased portable device screen resolution, the requirement of the high-definition video is increasing in today's world. In order to achieve better coding efficiency than H.264/AVC [1], some motion estimation algorithms are proposed to reduce the coding complexity while maintaining its high quality [2–4]. High efficiency video coding (HEVC) [5], also known as H.265, is developed by Joint Collaborative Team on Video Coding (JCT-VC) consisting of MPEG (Motion Picture Expert Group) and VCEG (Video Coding Experts Group). The structure of HEVC is similar to that of H.264/AVC, but it incorporates numerous advances, including quadtree structure, merge mode, sample adaptive offset, etc. Thanks to these advances, it achieves better video quality, or saves 50% bitrate compared with H.264/AVC. Many papers have been proposed to enhance the coding performance and applications of HEVC. Goswami *et al.* [6] proposed a fast algorithm to reduce the encoding time of HEVC through texture-based analysis. In [7], a rate control mechanism is proposed to improve the bitrate accuracy and visual quality in HEVC. Usman *et al.* [8] proposed a secure, lightweight, energy-efficient and robust scheme which considers HEVC intra-encoded video streams as sources for data exchange between the mobile users and the media clouds.

HEVC defines three frame types, including I-, P-, and B-frames. I-frame plays an important role because the position of I-frame is the first encoded frame in a group of picture (GOP). It is encoded by using only intra coding and without using any other frame as reference. The B- and P-frames refer to the previous encoded frames to encode. In HEVC, the distance between two I-frames is called intra-period. HEVC encodes frames with a fixed intra-period. In HEVC, intra-period is set as 32 in common. However, using fixed intra-period to encode the sequence with the scene changes may require more bits. Figure 1 is the illustration of the above case.

Figure 1 shows the position of scene change frame located behind of the frame that is encoded as I-frame, which causes the scene change frame not able to find a good reference block. The visual quality of the reconstructed scene change frame and those frames using scene change frame as a reference are lower. H.264/AVC also has this problem and some methods on this issue for H.264/AVC are proposed. Lee *et al.* [9] proposed an I-frame decision method based on entropy of the block histogram. Ding *et al.* [10] employ the sum of transform difference to detect a scene change. These methods use different measurements to calculate the complexity of frames. When the value of measurement is larger or smaller than a predetermined threshold, the current frame is assigned as I-frame. However, these methods need to set a predetermined threshold to encode the sequences with different contents, and it is not guaranteed that the

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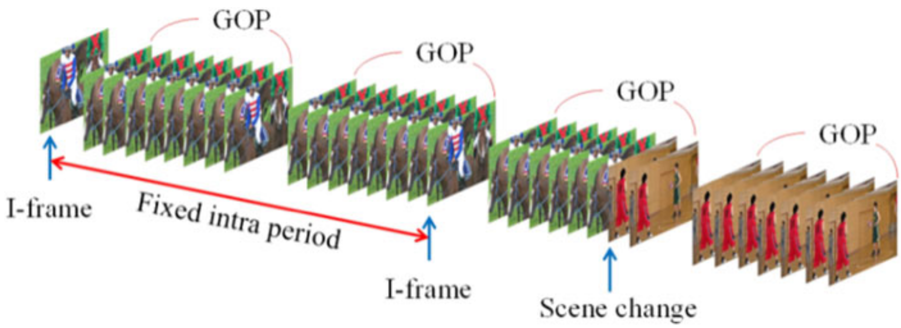

Fig. 1. Example of the fixed intra-period.

predetermined threshold is suitable for every sequence. For HEVC, research about the I-frame assignment method is lacking. Therefore, this paper proposes an I-frame assignment method based on Nash bargaining solution (NBS) in game theory for HEVC. Game theory [11] is the study about the interactive behavior of each player. Miranda *et al.* [12] present a study of the conjunction of possibility measures based on game theory. Moreover, game theory has been successfully applied to resource allocation problems solving and analyzing in the fields of bioinformatics application, channel coding, peer-to-peer system, sensor networks, and particle swarm optimization [13–17]. In [18–20], game theory is applied to video coding. The pioneering work regarding game theory based rate control is proposed in [18]. The macroblocks of a frame compete for limited bits. The utility function is used to represent the preference of each macroblock. Based on NBS, a fair bit allocation is achieved. In [19], a frame level rate control for scalable video coding is proposed. It considers the quality dependency between different temporal levels, and bits are allocated for each frame based on NBS. Yeh *et al.* [20] proposed the largest coding unit (LCU) level bit allocation method for HEVC rate control. The structural similarity (SSIM) index is used to measure the distortion between the original frame and encoded frame. The R-SSIM is used to define the utility function for each LCU. Nash equilibrium is used to achieve the better bit allocation between the LCUs of a frame.

This paper regards the I-frame assignment problem as a resource allocation problem and formulates it by special game model, called as bargaining game. The bargaining game is a multiple-player game which is used to model the bargaining interactions. It is also regarded as a nonzero-sum two-player game. A two-player bargaining game is represented by a pair U, d, where the feasible utility set $U \subset R^2$ is a compact and convex set. For any $u = (u_1, u_2) \in U$, such that $u > d$, i.e. $u_1 > d_1$ and $u_2 > d_2$ [21]. Based on different assumptions, many solutions have been proposed such as NBS, generalized NBS, Kalai–Smorodinsky bargaining solution [22], and

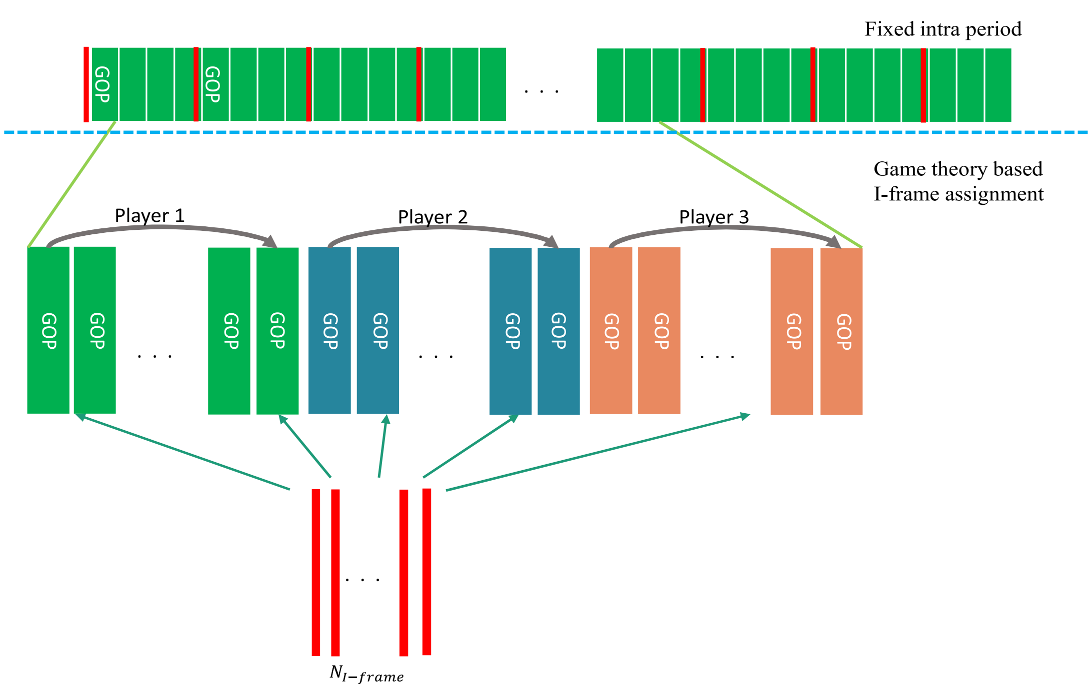

Fig. 2. Illustration of the proposed method.

Egalitarian bargaining solution. The generalized NBS is a unique bargaining solution that satisfied efficiency, linearity, independence of irrelevant alternatives axiom, which solves the generalized Nash product:

II. PROPOSED GAME THEORY BASED I-FRAME ASSIGNMENT METHOD

This section first describes the I-frame assignment problem. Suppose a sequence contains N_f frames with the fixed intra-period and random access configuration; this sequence includes $(N_f-1)/8$ GOPs and only has $(N_f-1)/32$ intra-periods. The number of I-frames is equal to the number of intra-periods, so the I-frame assignment problem is which frame should be assigned as I-frame to maximize the overall coding efficiency. The first frame and the first GOP of the sequence are not considered in the game model. Here, we denote the number of the GOP and I frame used in the game model as N_{GOP} and N_I, respectively. The I-frame assignment problem is formulated as follows. Figure 2 shows the concept of the proposed method.

A) Problem formulation

Player: The set of frames S contains the first frame of all GOPs in a sequence, i.e. $S=\{f_i|i=1,\ldots,N_{GOP}\}$ where f_i is the first frame of ith GOPs. S is averagely divided into N_p subsets as $P_1,\ldots,P_{N_p}$ such that $P_i=\{f_{(i-1)\cdot((N_{GOP}/N_p)+1)},\ldots,f_{i\cdot(N_{GOP}/N_p)}\}$. Each subset P_i is regarded as a player.

Strategies: The strategy represents the number of I-frames in the subset. Suppose the n_i is the strategy of player i and the total number of I-frames is N_I. An inequality constraint equation is formulated as follows:

$$\sum_{i=1}^{N_p} n_i \leq N_I. \tag{1}$$

Preference: Define that each player i has a mapping of a utility function u_i to reflect its preference. The correlation coefficient of the two frames represents the similarity between the two frames. The correlation coefficient of two frames j and k is defined as:

$$C_{j,k}=\frac{\mathrm{cov}(f_j,f_k)}{\sigma_{f_j}\sigma_{f_k}}. \tag{2}$$

where $\mathrm{cov}(f_j,f_k)$ is the covariance between the pixel values of the frame j and k, σ_{f_j} and σ_{f_k} are the standard deviations of the pixel values of the frame j and k. For each player i has a list $L_i=\{\omega_{i,j}|j=1,\ldots,N_{GOP}/N_p\}$ where $\omega_{i,j}$ is the frame index. The frame indexes in each list are arranged in ascending order of the correlation coefficient, i.e. $C_{\omega_{i,j},\omega_{i,j}-1}\leq C_{\omega_{i,j+1},\omega_{i,j+1}-1}$. For each player i, the frames $f_{\omega_{i,1}},\ldots,f_{\omega_{i,n_i}}$ may be assigned as I-frame.

In Fig. 3, suppose that the P_i contains the frames j to l. The $u_i(1)$ is calculated as:

$$u_i(1)=\frac{\sum_{a=j}^{\omega_{i,1}-2}C_{a,a+1}+\sum_{a=\omega_{i,1}}^{l-1}C_{a,a+1}}{l-j}. \tag{3}$$

Only the correlation coefficient of the frames $\omega_{i,1}-1$ and $\omega_{i,1}$ is not calculated, so equation (3) is also equal to

$$\begin{aligned}u_i(1)&=\frac{\sum_{a=j}^{\omega_{i,1}-2}C_{a,a+1}+\sum_{a=\omega_{i,1}}^{l-1}C_{a,a+1}}{l-j}\\&=\frac{\begin{array}{c}\sum_{j=1}^{(N_{GOP}/N_p)-1}C_{(i-1)\cdot((N_{GOP}/N_p)+j),(i-1)\cdot((N_{GOP}/N_p)+j)+1}\\-C_{\omega_{i,1}-1,\omega_{i,1}}\end{array}}{l-j}.\end{aligned} \tag{4}$$

Therefore, the general form of the utility function is defined as:

$$u_i(n_i)=\frac{\begin{array}{c}\sum_{j=1}^{(N_{GOP}/N_p)-1}C_{(i-1)\cdot((N_{GOP}/N_p)+j),(i-1)\cdot((N_{GOP}/N_p)+j)+1}\\-\sum_{k=1}^{n_i}C_{\omega_{i,k-1},\omega_{i,k}}\end{array}}{l-j+1-n_i}. \tag{5}$$

The utility function is defined as the average of correlation coefficients. When a player is assigned more I-frames, the utility of this player will increase.

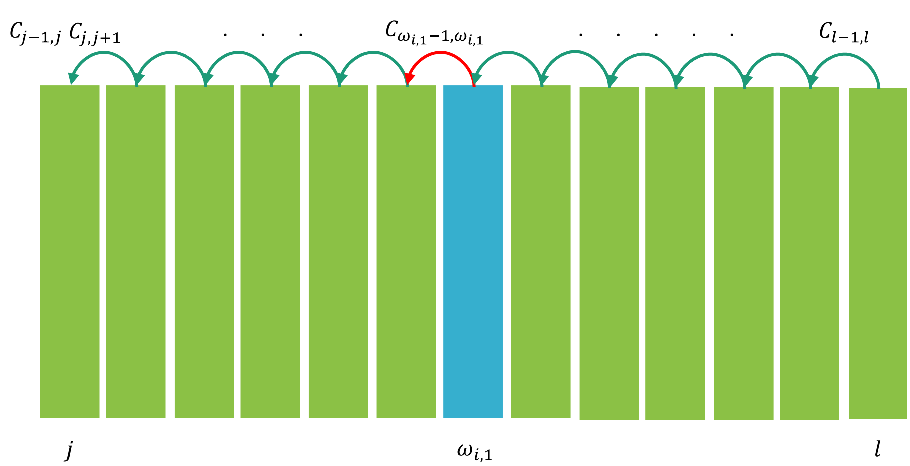

Fig. 3. Example of the calculation of the correlation coefficient.

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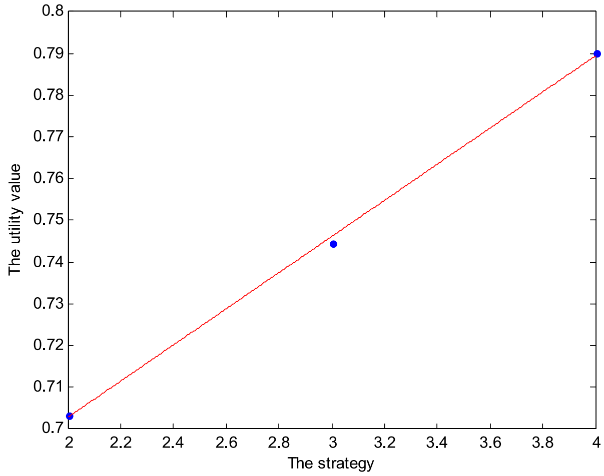

Fig. 4. The curve of the utility function.

Minimum utility: The minimum utility of the player i is denoted by d_i which is used to guarantee the visual quality. Each player i requests n_i^{min} to achieve the minimum utility, so $n_i > n_i^{min}$.

For example, a sequence is divided into several subsequences that contain 336 frames. Each subsequence is regarded as a game. Each game contains three players and 10 I-frames. Each player has 14 frames and competes for limit I-frames. Define that n_i is ranged from 2 to 4. Figure 4 shows the curve of the utility function, which is an approximately linear function. The utility function is formulated as follows:

$$u_i(n_i) = a_i \cdot n_i + b_i, \tag{6}$$

where a_i and b_i are the model parameters.

B) I-frame assignment with Nash bargaining solution

Based on game theory, the optimal I-frame allocation can be solved as follows to obtain the NBS:

$$\begin{aligned} & max \prod_{i=1}^{3} \left(u_i\left(n_i\right) - u_i\left(n_i^{min}\right)\right)^{p_i}, \\ & \text{such that} \sum_{i=1}^{3} n_i \leq 10, \quad n_i^{min} < n_i < n_i^{max}, \end{aligned} \tag{7}$$

where p_i is the weight of each player i, so $p_i = 1/u_i(0)$. Using equation (7) to formulate the I-frame assignment problem, it does not need to set the predetermined threshold. In addition, each player is assigned at least n_i^{min} I-frames to keep the visual quality.

Because

$$\begin{aligned} u_i((1-\alpha)x + \alpha y) &= a_i(1-\alpha)x + a_i\alpha y + b_i \\ &= (1-\alpha)u_i(x) + \alpha u_i(y) \end{aligned} \tag{8}$$

for any x and $y \in \mathbf{R}, x \neq y, \alpha \in [0,1]$, $u_i(n_i)$ is concave.

Since u_i is concave and injective, $\ln(u_i)$ is strictly concave. Then equation (7) can be represented in the following form:

$$\begin{aligned} & max \sum_{i=1}^{3} p_i \cdot \ln\left(u_i\left(n_i\right) - u_i\left(n_i^{min}\right)\right), \\ & \text{such that} \sum_{i=1}^{3} n_i \leq 10, \quad n_i^{min} < n_i < n_i^{max}. \end{aligned} \tag{9}$$

The above optimization problem can be solved by using Kuhn and Tucker theorem [23, 24]. This theorem is a generalized method of Lagrange multipliers. When some regularity conditions are satisfied, a solution in nonlinear programing can be optimized by adding Lagrange multipliers. Equation (8) can be reformulated as:

$$\begin{aligned} J = & \sum_{i=1}^{3} p_i \cdot \ln\left(u_i\left(n_i\right) - u_i\left(n_i^{min}\right)\right) + \lambda\left(10 - \sum_{i=1}^{3} n_i\right) \\ & + \sum_{i=1}^{3} \theta_i\left(n_i - n_i^{min}\right) + \sum_{i=1}^{3} \varepsilon_i\left(n_i^{max} - n_i\right), \end{aligned} \tag{10}$$

where λ, θ_i, and ε_i are the Lagrange multipliers. Then, the optimized solution can be obtained by solving equation (10):

$$\begin{cases} \dfrac{\partial J}{\partial r_i} = \dfrac{\partial p_i \cdot \ln\left(u_i\left(n_i\right) - u_i\left(n_i^{min}\right)\right)}{\partial n_i} - \lambda + \theta_i - \varepsilon_i = 0 \\ \dfrac{\partial J}{\partial \lambda} = 10 - \displaystyle\sum_{i=1}^{3} n_i \geq 0 \\ \lambda \dfrac{\partial J}{\partial \lambda} = \lambda\left(10 - \displaystyle\sum_{i=1}^{3} n_i\right) = 0 \\ \theta_i \dfrac{\partial J}{\partial \theta_i} = \theta_i\left(n_i - n_i^{min}\right) = 0 \\ \varepsilon_i \dfrac{\partial J}{\partial \varepsilon_i} = \varepsilon_i\left(n_i^{max} - n_i\right) = 0 \end{cases}, \tag{11}$$

where $i \in 1, 2, \ldots, N$.

We assume that $n_i - n_i^{min} > 0$, $n_i^{max} - n_i > 0$, and $\sum_{i=1}^{3} n_i = 10$, so $\theta_i = 0$, $\varepsilon_i = 0$ and $\lambda \neq 0$. Based on equation (10), $\partial J/\partial n_i$ can be simplified as shown in equation (11):

$$\begin{aligned} \frac{\partial J}{\partial n_i} &= p_i \cdot \frac{\partial \ln\left(u_i\left(n_i\right) - u_i\left(n_i^{min}\right)\right)}{\partial n_i} - \lambda \\ &= p_i \cdot \frac{\partial \ln\left(a_i \cdot n_i + b_i - a_i \cdot n_i^{min} - b_i\right)}{\partial n_i} - \lambda \\ &= \frac{p_i}{\left(n_i - n_i^{min}\right)} - \lambda = 0. \end{aligned} \tag{12}$$

n_i can be represented as:

$$n_i = \frac{p_i}{\lambda} + n_i^{min}. \tag{13}$$

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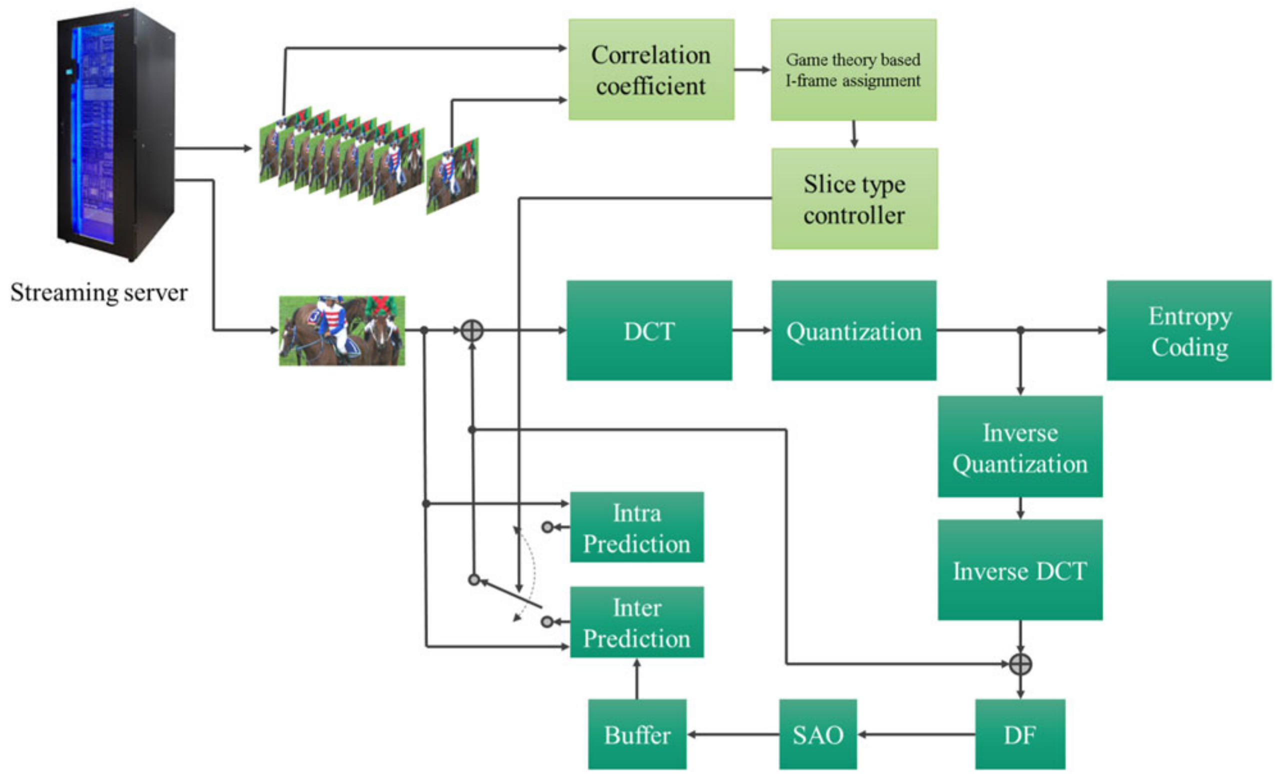

Fig. 5. Flowchart of the proposed method for video streaming service.

Table 1. Information on testing sequences.

Testing sequences	The components of each testing sequence
D1	*BasketballPass* (frame 1–50) + *BQSquare* (frame 1–50) + *BlowingBubbles* (frame 1–50) + *RaceHorses* (frame 1–50) + *BasketballPass* (frame 51–100) + *BQSquare* (frame 51–100) + *BlowingBubbles* (frame 51–100)
D2	*BasketballPass* (frame 1–50) + *BQSquare* (frame 1–60) + *BlowingBubbles* (frame 1–70) + *RaceHorses* (frame 1–80) + *BasketballPass* (frame 51–140)
D3	*BasketballPass* (frame 1∼90) + *BQSquare* (frame 1∼80) + *BlowingBubbles* (frame 1∼70) + *RaceHorses* (frame 1∼60) + *BasketballPass* (frame 91∼140)
C1	*BasketballDrill* (frame 1–50) + *BQMall* (frame 1–50) + *PartyScene* (frame 1–50) + *RaceHorses* (frame 1–50) + *BasketballDrill* (frame 51–100) + *BQMall* (frame 51–100) + *PartyScene* (frame 51–100)
C2	*BasketballDrill* (frame 1–50) + *BQMall* (frame 1–60) + *PartyScene* (frame 1–70) + *RaceHorses* (frame 1–80) + *BasketballDrill* (frame 51–140)
C3	BasketballDrill (frame 1–90) + BQMall (frame 1–80) + PartyScene (frame 1–70) + RaceHorses (frame 1–60) + BasketballDrill (frame 91–140)
B1	*Kimono1* (frame 1–50) + *ParkScene* (frame 1–50) + *Kimono1* (frame 51–100) + *ParkScene* (frame 51–100) + *Kimono1* (frame 101–150) + *ParkScene* (frame 101–150) + *Kimono1* (frame 151–195)
B2	*Cactus* (frame 1–50) + *BasketballDrive* (frame 1–50) + *Cactus* (frame 51–100) + *BasketballDrive* (frame 51–100) + *Cactus* (frame 101–150) + *BasketballDrive* (frame 101–150) + *Cactus* (frame 151–195)

Table 2. Simulation setting in HEVC.

Item	Description of setting
Number of frames	345 frames
Coding structure	Random access
QP	22, 27, 32, 37
Rate control	Disable

Table 3. Comparisons of BD-BR (%) and BD-PSNR (dB).

		Proposed versus FIP		EIFA versus FIP	
Class	Sequence	BD-BR (%)	BD-PSNR (dB)	BD-BR (%)	BD-PSNR (dB)
D	D1	−6.25	0.29	−0.58	0.03
	D2	−5.18	0.24	−1.84	0.08
	D3	−5.02	0.23	−1.63	0.07
C	C1	−5.18	0.21	−1.52	0.06
	C2	−5.35	0.22	−2.04	0.08
	C3	−4.30	0.17	−0.64	0.02
B	B1	−6.30	0.20	−2.47	0.07
	B2	−6.53	0.18	−0.23	0.01
	Average	−5.51	0.22	−1.37	0.05

By substituting equation (12) into $\sum_{i=1}^{3} n_i = 10$, $(1/\lambda)$ can be represented as

$$\frac{1}{\lambda} = \frac{1}{\sum_{i=1}^{N} p_i}\left(10 - \sum_{i=1}^{3} n_i\right). \tag{14}$$

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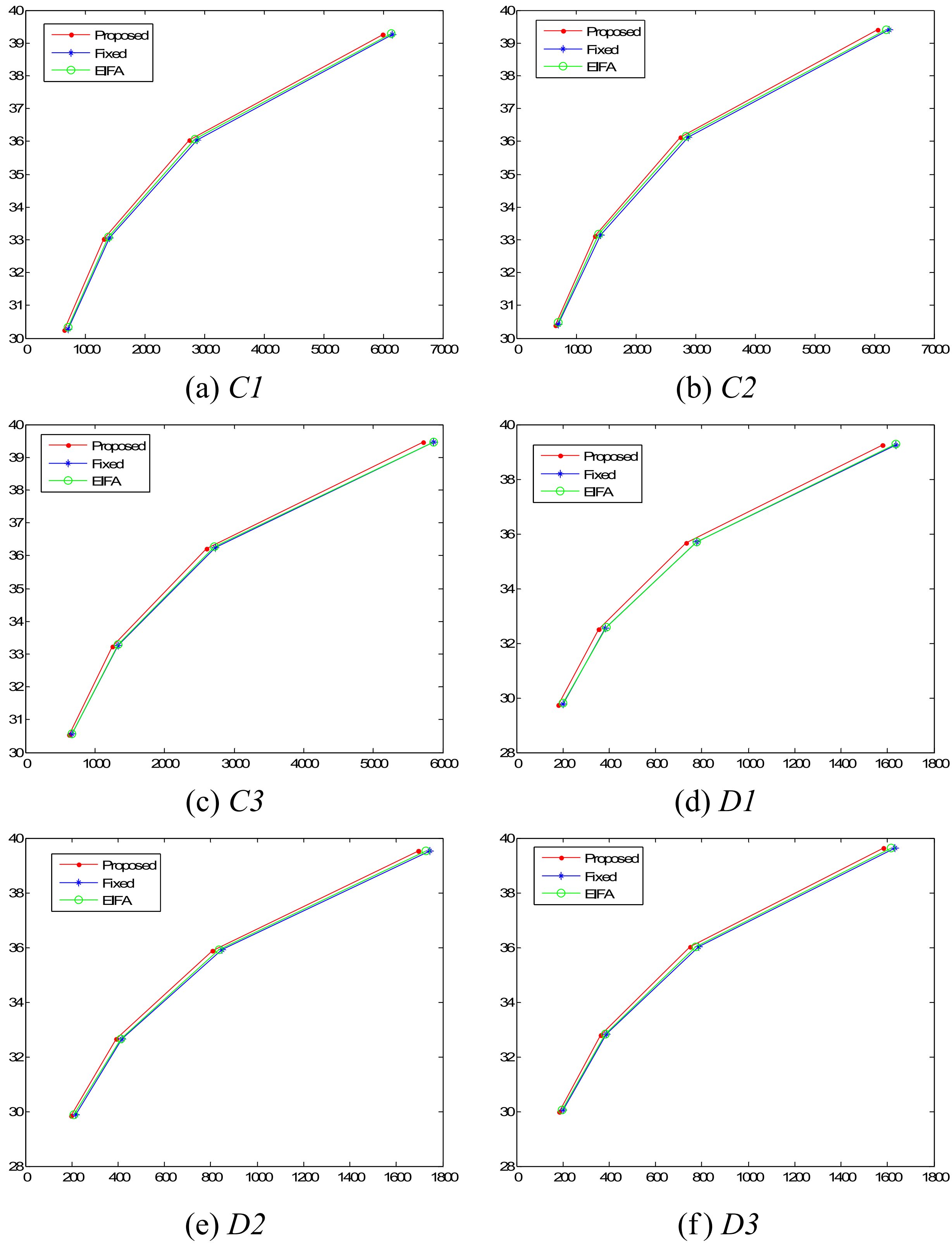

Fig. 6. Comparisons of RD curves.

Therefore,

$$n_i = min\left(\frac{p_i}{\sum_{j=1}^{N} p_j}\left(10-\sum_{i=1}^{3} n_i\right)+n_i^{min}, n_i^{max}\right), \qquad (15)$$

where n_i^{min} and n_i^{max} are determined by experimental experience, in our experiment, the n_i^{min} and n_i^{max} are set as 2 and 4. The set of I-frame S_I is defined as:

$$S_I = \{f_{\omega_{1,1}}, \ldots, f_{\omega_{1,n_1}}, f_{\omega_{2,1}}, \ldots, f_{\omega_{2,n_2}}, f_{\omega_{3,1}}, \ldots, f_{\omega_{3,n_3}}\}. \qquad (16)$$

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For real-time applications, it is not acceptable that the proposed method needs a large frame recorder and an initial delay to storage enough sampling frames. However, it is acceptable for a video streaming service. Figure 5 shows the flowchart of the proposed method for a video streaming service. A buffer uses to store the frames accessed from the streaming server. In the initial stage, the first nine frames will be accessed to be stored in the buffer. In the first stage, the correlation coefficient of the first and the ninth frames in the buffer will be calculated and recorded. The first eight frames in the buffer will be removed, and the next eight frames will be stored in the buffer. The stage mentioned above is repeated until the number of the recorded correlation coefficient is enough. In the second stage, the I-frame assignment problem will be solved by using the proposed method. The third stage is to encode the subsequence. Repeat these three stages until the encode process is finished.

III. EXPERIMENTAL RESULTS

Experimental results are provided in this section to evaluate the performance of the proposed method. We combine different video sequences to generate six testing sequences. The components of each testing sequences are shown in Table 1. The test sequences D1, D2, and D3 are combined by different test sequences in class D, and the test sequences C1, C2, and C3 in class C. The resolution of the class D and class C is 416×240 and 832×480 pixels, respectively. The proposed method is implemented in HEVC reference software HM15.0 [25] and compared with the estimated I-frame assignment (EIFA) method and the fixed intra-period assignment (FIP). The EIFA method assigns the first frame of the current GOP as I-frame if the correlation coefficient of the first frames of the current GOP and the previous GOP is smaller than the predetermined threshold or the distance between the previous I-frame and the first frames of the current GOP is equal to 32. Other detailed simulation settings are shown in Table 2.

Table 3 shows the comparisons of the BD-BR and BD-PSNR [26] performance of the EIFA method and the proposed method with respect to the FIP method. Averagely, the proposed method shows 5.21% reductions on BD-BR, or 0.22 dB gain on BD-PSNR. The EIFA method shows 1.38% reduction on BD-BR, or 0.06 dB gain on BD-PSNR.

The rate-distortion (RD) curves of three methods with different testing sequences are shown in Fig. 6. By observing the RD curves in Fig. 6, the proposed method clearly achieves better coding performance when compared to the EIFA method and the FIP method.

IV. CONCLUSION

This paper proposes a new I-frame assignment method based on NBS in HEVC. In the proposed method, the encoded sequence is divided into several subsequences and each subsequence is regarded as a game. All GOPs in a subsequence is further divided into several sets of GOP. Each set of GOP is regarded as a player and competes for limit I-frames. The correlation coefficient of the two frames is used to calculate the utility function of each player. The optimal I-frame assignment is determined based on the generalized NBS. Experimental results show the proposed method outperforms HEVC by 5.21% bitrate saving.

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