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Fast Multiple Frame Selection For H.265/HEVC Standard Based On Data Mining

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ABSTRACT
The new H.265/HEVC video coding standard promotes the realization of 4K/8K ultrahigh definition (UHD)video applications. To improve the coding efficiency, H.265/HEVC allows motion estimation (ME) performing on multiple reference frames (MRF).Although the MRF can enhance the performance and allow the encoder to search a better reference frame from several previous pictures, the computational complexity of the MRF-based ME(MRF-ME) module dramatically increases. To accelerate the process of MRF prediction, we propose a fast MRF-ME algorithm based on data mining to speed up encoding process of H.265/HEVC encoder. Firstly, we find that there is a high temporal-spatial correlation existing in the MRF. Then, we find appropriate attributes from MRF-ME module and extract the corresponding data. We save these attributes as an attribute-relation file format (ARFF).Then, the ARFF is performed on WEKA [9] to train the MRF-ME decision trees. Finally, we employ the created decision trees to achieve fast selection of the multiple reference frames. Simulation results show that the proposed method can achieve an average time improving ratio (TIR) with MRF=4 and MRF=8about 70.09% and 82.49%as compared to H.265/HEVC test platform (HM16.7), respectively. It is clear that the proposed method can efficiently reduce the computational complexity of MRF-ME process inH.265/HEVC encoder with insignificant loss of image quality.
KEYWORDS*–Video coding standard, Data mining, Motion estimation.*

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I INTRODUCTION

The High efficiency video coding (HEVC), also known as H.265, is the newest video encoding standard for 4K/8K ultrahigh definition (UHD) video applications [1-2]. H.265/HEVC can achieve an average bit rate decrease of 50% in comparison with H.264/AVC High Profile while still maintaining the same subjective video quality [3]. This is because H.265/HEVC adopts some new coding structures including coding unit (CU), prediction unit (PU) and transform unit (TU). The CU is the basic unit of region splitting used for inter/intra prediction, which allows recursive subdividing into four equally sized blocks. The CU can be split by coding quadtree structure of 4 level depths, which CU size ranges from largest CU size of 64×64 pixels to the smallest CU size of 8×8 pixels. At each depth level (CU size), H.265/HEVC performs motion estimation (ME) and motion compensation (MC) with different size. The PU is the basic unit used for carrying the information related to the prediction processes, and the TU can be split by residual quadtree (RQT) at maximally 3 level depths which vary from 32×32 to 4×4 pixels. The relationship among the CU, PU and TU is shown in Fig.1.

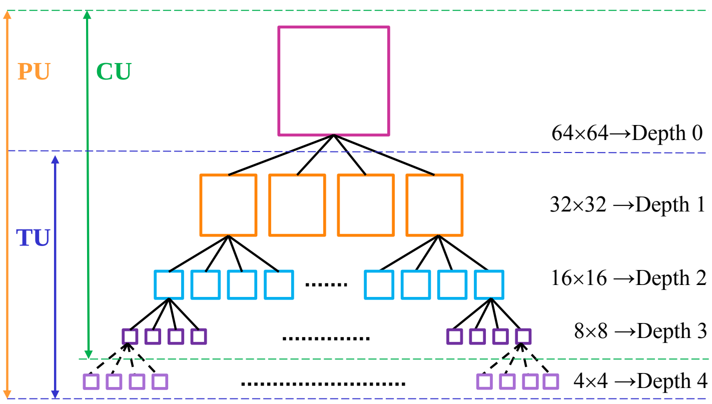

Fig. 1. The relationship among the CU,PU and TU.

In general, intra-coded CUs have only two PU partition types including 2N×2N and N×N but inter-coded CUs have eight PU types including symmetric blocks (2N×2N,2N×N, N×2N, N×N) and asymmetric blocks (2N×nU, 2N×nD, nL×2N, nR×2N) [1]. The rate distortion costs(RDcost) have to be calculated by performing the PUs and TUs to select the optimal partition mode under all partition modes for each CU size. In the PU structure, H.265/HEVC adopts ME module to choose the optimal inter prediction mode. In order to improve the accuracy of PU prediction, multiple reference frames (MRF) interframe prediction is performed in the ME module for H.265/HEVC. Suppose that four reference indexes (RefIdx) of frames are used, the selecting process of inter prediction mode using MRF-based ME (MRF-ME)is shown in Fig. 2.We can summarize the decision process of inter prediction mode. Firstly, H.265/HEVC adopts the coding tree unit (CTU), and each CTU allows recursive splitting into four equal CU. And then, the PU performs the inter prediction processes. When pruning the best CTU coding quadtree, the inter prediction module executes 7 different prediction modes to find the best partition mode after MRF-ME procedure.

Although the MRF-ME can enhance the PU performance and allow the encoder to search a better reference frame from several previous pictures, the computational complexity of the MRF-ME dramatically increases. Therefore, the very high computational complexity becomes a main bottleneck for the real-time applications of H.265/HEVC in UHD videos, such as live video broadcasting, mobile video communication and video surveillance.

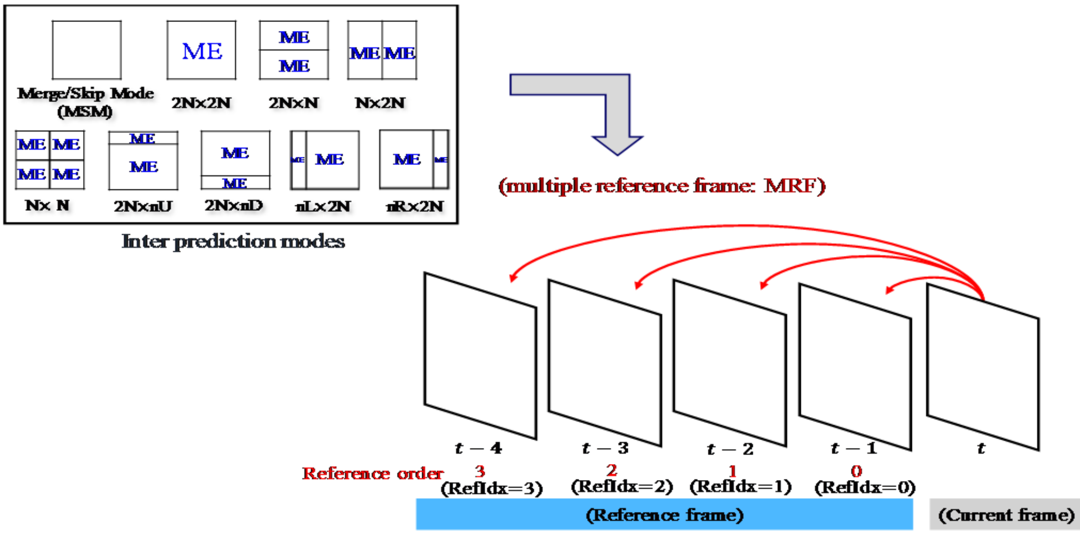

Fig. 2.The selecting process of inter prediction mode using MRF scheme.

In order to reduce the computational complexity of MRF-ME module in H.265/HEVC, Yang et al. proposed a H.265/HEVC fast reference picture selection recently [4]. After the statistical analysis in performing MRF-ME encoding process, they found that a high correlation exists between the best reference frame and lowest rate-distortion cost (RD cost) associated with advanced motion vector prediction (AMVP). Therefore, they use the predefined threshold to determine whether the AMVP-selected reference frame is the best reference frame. However, the predefined threshold is inefficient when the video sequence with active motion and complicate background. To combat these problems, an alternative solution is proposed to use an intelligent approach based on machine learning technique from intermediate encoding results to select the best frame [5-7]. Therefore, to further improve the accuracies of MRF prediction, we propose a fast MRF-ME algorithm based on data mining to speed up encoding process of HEVC encoder. Firstly, we find that there is a high temporal-spatial correlation existing in the MRF. Then, we find appropriate attributes from MRF-ME module and extract the corresponding data, and save these attributes as an Attribute-Relation File Format (ARFF). And then, the ARFF is performed onWaikato Environment for Knowledge Analysis (WEKA) [8] to train the ME-MRF decision trees using the C4.5 algorithm [9]. Finally, we employ the created decision tree to achieve the fast selection of multiple reference frames.

II MRF-ME ENCODING PROCESS ON THE H.265/HEVC

In order to further improve the coding efficiency, the H.265/HEVC standard employs AMVP algorithm to design the best MV predictor for the current PU. The AMVP algorithm produces initial MVs (IMVs) for all the reference frames for a PU. An IMV is chosen from the available MVs of spatially neighboring or temporally collocated coded PUs of the current PU [10]. In other words, every reference frame in the MRF will produce one IMV. Figure 3 shows the encoding process of MRF-ME using four reference frames to find the best reference frame. We can simply describe the working procedure in MRF-ME module as follows. Firstly, the RD costs

(J_{AMVP}) associated with those IMVs from AMVP are evaluated and one best IMV with ($J_{AMVP}\_ref\_m$: m=0~3) is chosen for every reference frame. And then, the MRF-ME performs the ME to search the minimum RD cost ($J_{inter}\_ref\_m$:m=0~3) in every reference frame using the corresponding IMV and decides the best inter prediction mode. Finally, the MRF-ME selects the best reference frame according to the lowest RD cost (J_{inter}_min) among those four reference frames.

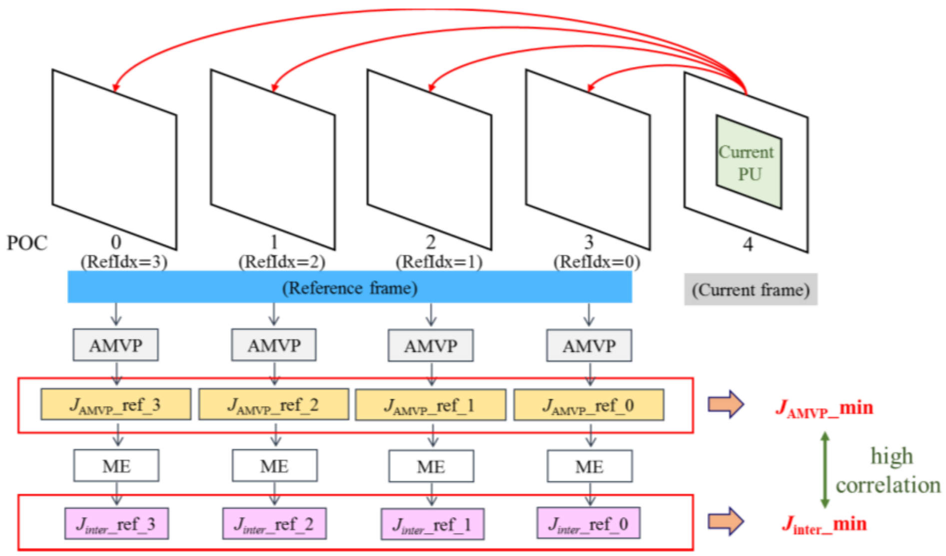

Fig. 3. The encoding process of MRF-ME on H.265/HEVC using four reference frames.

Although the MRF-ME improves the compression performance, the computational complexity increases in proportion to the number of reference frames. The ME is the most time-consuming computations in H.265/HEVC when performing exhaustive MV searching within the entire search range for all the reference frames. Moreover, the main target resolution of H.265/HEVC is 4K/8K UHD videos. Therefore, this leads to a big obstacle for real-time applications. To reduce the computational complexity of MRF-ME module in H.265/HEVC, Yang et al. found that there is a high correlation existing between the best reference frame (J_{inter}_min) and lowest RD cost associated with AMVP among those four frames(J_{AMVP}_min) [4]. Their simulation results reveal that the corresponding frame with J_{AMVP}_min is much more likely to be the optimal choice than the other reference pictures are. Since there is an average hit rate higher than 60% for J_{AMVP}_min =J_{inter}_min, the ME on the other reference frames can be avoided. However, their method suffers severely when the video sequence with active motion and complicate background.

III PROPOSED FAST ME-MRFBASED ON DATA MINING

In order to analyze the encoding complexity of selecting frame process of the MRF-ME. A series of statistical analysis is conducted to reveal the encoding features. H.265/HEVC standard provides 24 test video sequences of different resolutions, frame rate and scenarios [11]. We select 8 test sequences (BasketballDrill, BQMall, PartyScene, RaceHorses, BasketballPass, BQSquare, BlowingBubbles, RaceHorses, and RaceHorses), which possess different resolutions, motion activities and textures, to find useful attributes for data mining by using test platform HM16.7 [11].Quantization parameter (QP)is set to 32 and low delay (LD) encoder configuration is used in HM16.7.

3.1 MRF analysis and statistics

H.265/HEVC performs MRF-ME to improve the accuracy of PU prediction. Figure 4 is a statistical model which selects the best reference frame index (RefIdx_best) for PU module in each CU under different depths. The figure shows that the RefIdx=0 selected by PU module for different CU depths is the best reference frame index (i.e. RefIdx_best=0). Since most of characteristics of frame content are background or objects move slowly, the reference frame closest to the current frame is frequently selected as the best reference frame. We find an average of 86.8% PUs select *RefIdx*=0 as the RefIdx_best from Fig.4. Since the training of the binary decision trees is performed with C4.5 algorithm, we divide the best reference frame index (RefIdx_best) into two subsets which represent Class 0 (RefIdx_best=0) and Class 1 (RefIdx_best=1~3).

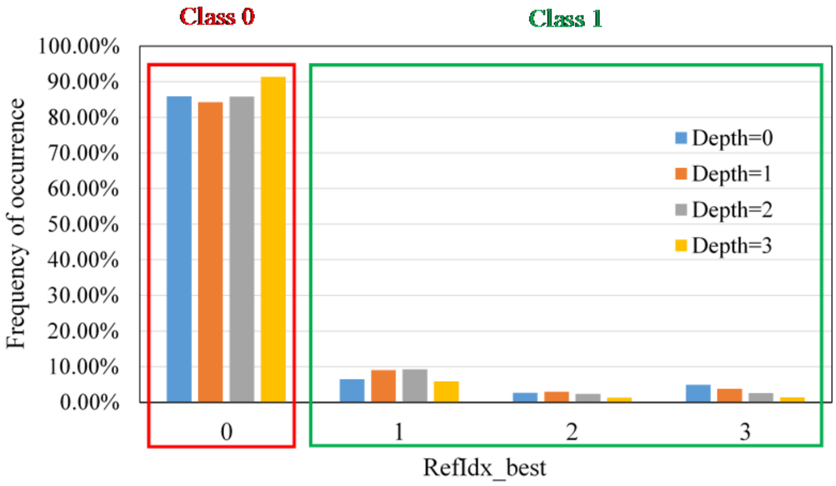

Fig. 4.Frequency of occurence of best reference frame index (RefIdx_best).

Because H.265/HEVC performs ME on MRF structure to find the best reference frame (RefIdx_best) in each PU as shown in Fig. 2, this will lead to reduce the encoding performance of PU module. Natural video sequences have strongly spatial and temporal correlations, especially in the homogeneous regions. The best reference frame of a current PU is the same as the RefIdx_best of its spatially adjacent PUs due to the high correlation between adjacent PUs. Therefore, we analyze and calculate the temporal and spatial correlation values of RefIdx_best from the temporal (co-located: Col) and spatial (left: L, above left: AL, above: A and above right: AR) neighboring blocks of the current PU as shown in Fig. 5. Table 1 shows the probability of the same RefIdx_best among the temporal (Col) and spatial (L, AL, A and AR) neighboring PUs of the current PU. From Table1, we can find that there is a high probability of the same RefIdx between current PU and neighboring PUs

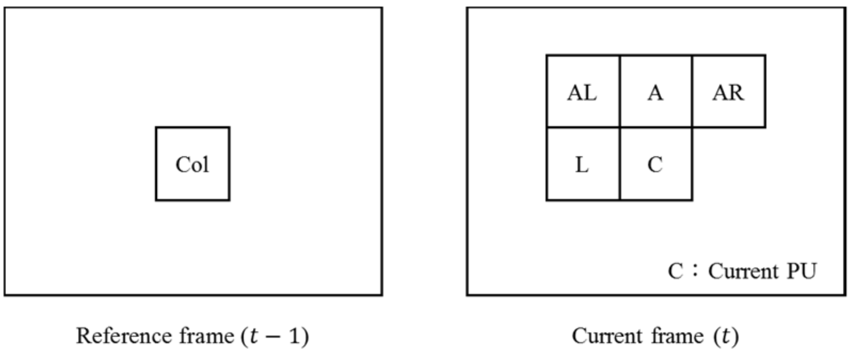

Fig. 5.Temporal and spatial correlation of PUs.

Table1. Probability of the same RefIdx between current PU and neighboring PUs (Depth=0，QP=32).

Probability / Sequences	P(L)%	P(AL)%	P(A)%	P(AR)%	P(Col)%
BasketballDrill	70.80	66.77	68.87	67.74	66.77
BQMall	85.72	82.94	83.83	82.72	82.21
PartyScene	78.49	73.98	76.56	72.74	71.57
RaceHorses	82.99	81.67	83.53	82.48	81.47
BasketballPass	82.39	81.20	80.22	75.43	81.85
BQSquare	57.17	47.72	48.70	47.50	40.00
BlowingBubbles	84.13	80.00	84.24	83.80	79.46
RaceHorses	95.87	94.89	95.00	95.33	92.28
Average	79.70	76.14	77.62	75.94	74.45

3.2 Attributes analysis and selections

The partitioning structures to early termination for selecting best reference frame in MRF-ME, binary coding trees play a main role due to their interdependence with the remaining partitioning structures. The early termination consists in deciding whether the splitting of PUs into two classes which belong to Class 0 or Class 1 should be tested. The key problem using data mining to fast select the best reference frame is how to find appropriate attributes from MRF-ME and extract the corresponding data. Therefore, we first consider the impact of *RefIdx_* J_{AMVP}*_min* on the MRF-ME module for the current PU. Figure 6 shows thatthe frequency of occurrence when the best reference frame index(*RefIdx_best*) is the same as *RefIdx_* J_{AMVP}*_min* for PU (2N×2N).The curves show that there is a clear relation between the relation between *RefIdx_best* and*RefIdx_* J_{AMVP}*_min*. WEKA can compute these thresholds for each attribute for every different size PU during the process of training the decision trees.

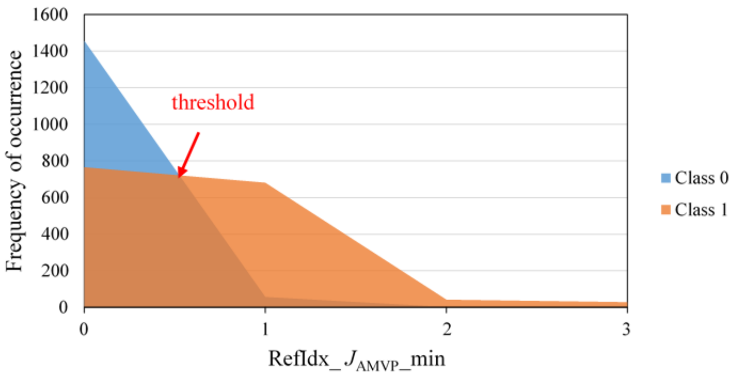

Fig. 6.The frequency of occurrence when *RefIdx_best* =*RefIdx_* J_{AMVP}*_min*.

To further improve the accuracy of the best reference frame, we use the correlation exists in the AMVP and *RefIdx_best*. According to the previous analysis, the final attributes selected in the training process to split Class0 or Class 1 for fast MRF-ME process are as follows:

$$Ratio_{AMVP}(\text{Class1}, \text{Class0}) = \frac{J_{AMVP}\_Class1}{J_{AMVP}\_Class0} \tag{1}$$

$$relRatio_{AMVP}(Class1, Class0) = \left|\frac{J_{AMVP}\_Class0 - J_{AMVP}\_Class1}{J_{AMVP}\_Class0}\right| \tag{2}$$

$$Ratio_{AMVP}(min, ref0) = \frac{J_{AMVP}\_min}{J_{AMVP}\_ref0} \tag{3}$$

$$relRatio_{AMVP}(min, ref0) = \left|\frac{J_{AMVP}\_min - J_{AMVP}\_ref0}{J_{AMVP}\_ref0}\right| \tag{4}$$

where the J_{AMVP}_Class0 and J_{AMVP}_Class1 are the values of J_{AMVP} which the AMVP-selected reference frame belongs to Class 0 or Class 1, respectively. The $relRatio_{AMVP}(Class1, Class0)$ and $relRatio_{AMVP}(min, ref0)$ values are the related normalized difference for $Ratio_{AMVP}(\text{Class1}, \text{Class0})$ and $Ratio_{AMVP}(min, ref0)$, respectively.

These above four attributes are selected which mainly consider the active motion and complicate background in video sequences. We take the attribute (1) to explain the characteristics of splitting decision for Class 0 and Class 1. Figure 7 shows the statistical model between *RefIdx_best* and $Ratio_{AMVP}(\text{Class1}, Class0)$ for the currentPU (64×64). When the value of $Ratio_{AMVP}(\text{Class1}, Class0)$ is greater than threshold, it represents that the low motion or very homogeneous image region. In other words, the probability of the *RefIdx_best* belonging to Class 0 is higher than Class 1. On the other hand, if the value is less than threshold, it represents a large change in the motion of the image, the probability that the *RefIdx_best* belongs to Class 1 is higher. Attributes (2)~(4) have the similar properties.

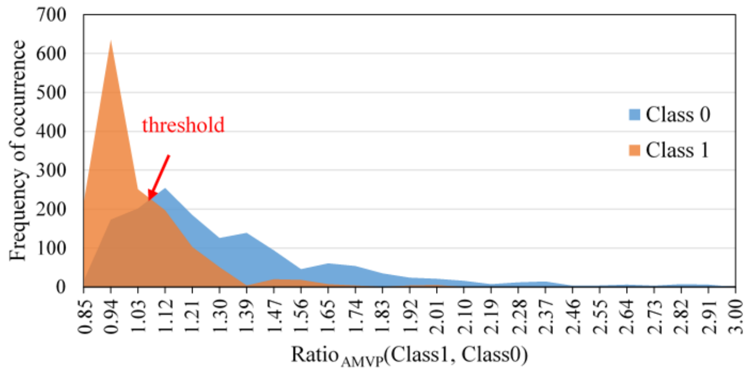

Fig. 7.The statistical model between *RefIdx_best* and $Ratio_{AMVP}(\mathbf{Class1}, \mathbf{Class0})$.

And then, we discuss the neighboring block attributes related with the coding tree to split decision for Class 0 or Class 1. Five neighboring PUs of the current PU according to Fig. 5 are selected to analyze the attribute for decision tree. Therefore, the value of all neighboring RefIdx average of spatial and temporal (*AllNeibRefIdxAvg_ST*) PUs is calculated and analyzed. Figure 8 displays the statistical model between *RefIdx_best* and *AllNeibRefIdxAvg_ST* for the current PU (64×64).

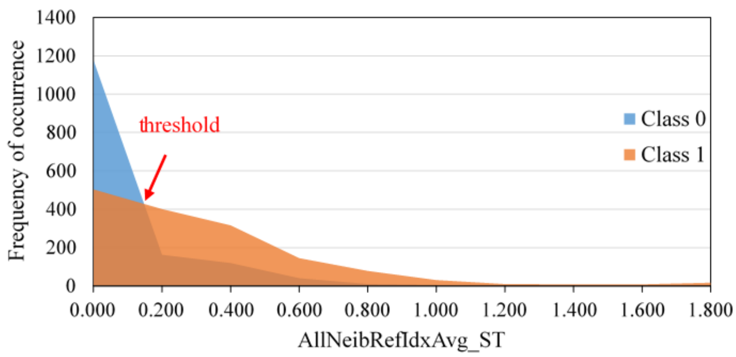

Fig. 8.The statistical model between RefIdx_best and AllNeibRefIdxAvg_ST.

Since the upper depth is related with the coding tree depth in neighboring CTUs already encoded, there is a high correlation of the *RefIdx_best* between the current PU depth and upper PU depth. Figure 9 displays the average occurrence probability of upper PU RefIdx (*upperPU_RefIdx*) in the current PU (64×64) depth splitting mode in the MRF-ME for CUs. From Fig.7, we can notice that the average occurrence probability has a unbalance distribution. There are also similar conclusions for other size(8×8,16×16 and 32×32) CUin PU structure.

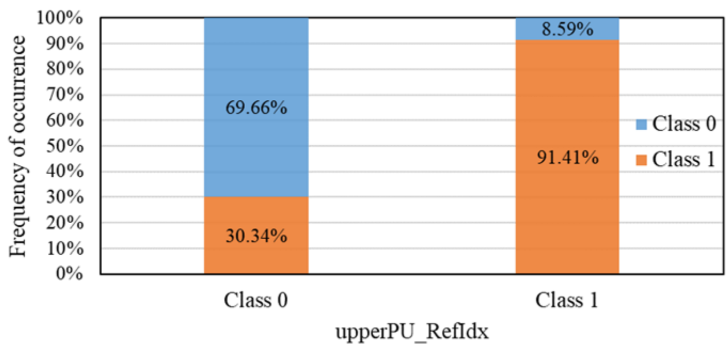

Fig. 9. Average occurrence probability of upper PU RefIdx (upperPU_RefIdx).

We further analyzed these features for MRF-ME coded 64×64 CUs in the training sequence coded with QP=32. And we can easily find that the frequency of occurrence of each PU which has the same *RefIdx_best* or the different *RefIdx_best* from seven selected attributes including *RefIdx_* J_{AMVP}*_min*, $Ratio_{AMVP}(\mathrm{Class1}, \mathrm{Class0})$, $relRatio_{AMVP}(Class1, Class0)$, $Ratio_{AMVP}(min, ref0)$, $relRatio_{AMVP}(min, ref0)$, *AllNeibRefIdxAvg_ST*and *upper PU_RefIdx*. Therefore, these attributes for MRF-ME as mentioned above are very suitable to build best decision trees. There are also similar conclusions for other size(8×8,16×16 and 32×32) CUin the proposed fast multiple frame selection.

3.3 Implementing decision trees

In this paper, we build 8 different decision trees from 4 CU size which separately includes 2N×2N and other PUs(others), as shown in Fig. 2. Therefore, these decision trees can be denoted as two types of 2N×2N and others for PU in each CU size (8×8, 16×16, 32×32, 64×64). The WEKA [8] was used to implement decision trees based on data mining. The ARFF files which are text files including a set of above attributes was used as input, and then we use WEKA to start machine learning to train the decision trees with the C4.5 algorithm [9].Finally, we can separately obtain8 decision trees for PU structure. A best 64×64 decision tree for other PU model in 64×64 CU size is shown in Fig.10.All reference decision trees can be found from the ftp website [12].

In order to evaluate the performance of decision trees, we made a test aimed at the decision tree accuracy. These results are shown in Table 2 which indicates the accuracy of each tree and other characteristics of the decision trees including their depth, the number of test nodes and the number of leaves. From Table2, we can find the decision trees have high accuracies. In other words, we can find a fast H.265/HEVC encoding when these decision trees are directly applied to our proposed MRF-ME. Among these8 decision trees for MRF-ME, the accuracy of 2N×2N decision tree is relatively lower than the others. This is because the number of 2N×2N features are less than the others. It has an obvious influence on accuracy according to the feature in different CU sizes. In addition, it is important to notice that all of decision trees are composed of less than 10 decision levels (depth). This means that the computational complexity added to the H.265/HEVC encoder associated with the decision trees is negligible.

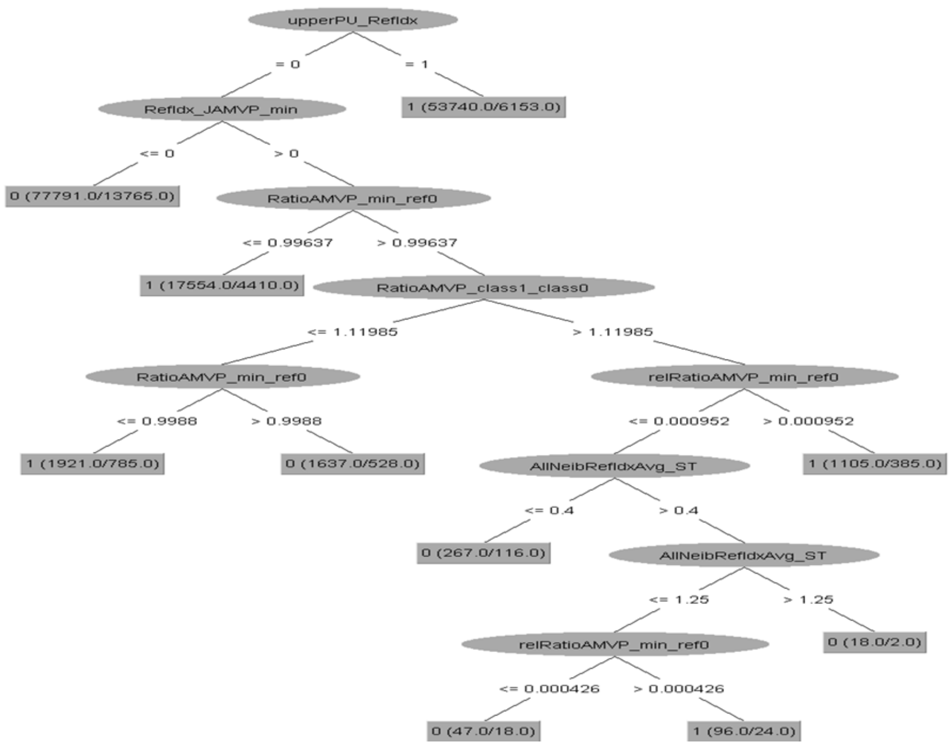

Fig. 10.64×64 decision tree for others in 64×64 CU size.

Table 2.Accuracy of decision trees for MRF-ME model.

CU size	PU size	Decision Accuracy (%)	Depth	Nodes	Leaves
64×64	2N×2N	79.66	9	12	13
	Others	82.95	8	9	10
32×32	2N×2N	78.50	9	14	15
	Others	80.14	6	7	8
16×16	2N×2N	78.52	10	13	14
	Others	80.86	5	8	9
8×8	2N×2N	79.69	10	17	18
	Others	85.62	5	7	8

3.4 Proposed fast multiple frame selection

The flowchart of proposed fast multiple frame selection in MRF-ME model for H.265/HEVC encoder based on data mining is shown in Fig.11.Firstly, H.265/HEVC compress the CTU in slice , and each CTU is recursive splitting into four equal CU to perform data compress. Then, the PU performs the inter prediction processes. To improve the coding efficiency, we employs AMVP algorithm to design the best MV predictor in MRF for the current PU. And then we can find the reference frames belong to Class 0 or Class1 using data mining according to those decision trees which have been established in the MRF-ME module. Finally, we run the MRF-ME to select the best reference frame according to the lowest RD cost among those reference frames.

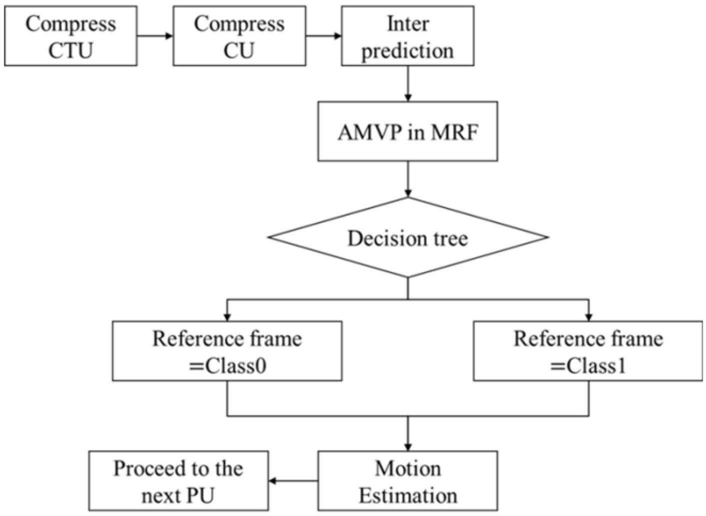

Fig.11. Flowchart of the proposed fast multiple frame selection.

IV EXPERIMENTAL RESULTS

The coding performances are evaluated by the comparisons of *Bjøntegaard-Delta* rate (BD-rate), *Bjøntegaard-Delta Peak Signal-to-Noise Ratio for Luma Y* (BD-PSNRY)[13] and time improving ratio (TIR)between Yang's method [4]. The proposed method is tested under the H.265/HEVC software platform (HM16.7) [11].For a fair comparison, we also implemented Yang's algorithm in same encoding environment. The TIR is defined as following

$$\mathrm{TIR} = \frac{\mathrm{TIME}_{\mathrm{HM16.7}} - \mathrm{TIME}_{\mathrm{method}}}{\mathrm{TIME}_{\mathrm{HM16.7}}} \times 100\% \qquad (5)$$

The system hardware is Intel (R) Core(TW) CPU i7-3350P @ 3.40 GHz, 8.0 GB memory, and Window XP 64-bit O/S. Additional details of the encoding environment are described in Table 3.

Tables4~5 show the performance comparisons between the proposed and Yang's method when performing 4 reference frames (MRF=4) and 8 reference frames (MRF=8) based on HM 16.7, respectively. As shown in the Table4, the proposed method and Yang's both can achieve average TIR about 43.64% and 70.09%, respectively. In addition, we also can find that the TIR of our method is more than Yang's method about 26%.On the other hand, Table 5 also shows the performances between the proposed method and Yang's with the same scenario for MRF=8. We also can find that the proposed method can achieve an average of TIR to 82.49 % more than Yang's method about 16%.It is clear that the proposed method can efficiently increase the speed of HEVC encoder with insignificant loss of bitrate-distortion cost. From Tables4~5, we can find that that the proposed fast multiple frame selection using data mining indeed efficiently reduce the computational complexity in MRF-ME module with insignificant loss of RD performance. In addition, It is very obvious when the higher the number of MRF is, the more the improvement of encoding speed is.

Table3.Test conditions and configuration parameters.

Test sequences	• Class A (2560×1600): Traffic, PeopleOnStreet • Class B (1920×1080): Kimono, ParkScene, BasketballDrill, BQMall, PartyScene
Total frames	48 frames
QP	22, 27, 32 and 37
Encoder	HM 16.7
Reference frames	4
Scenario	Low delay (IPPPP…)

Table.4.The performance comparisons between Yang's and the proposed method as MRF=4.

	BD-rate(%)		BD-PSNRY(dB)		TIRHM (%)	
Sequence	Yang	Proposed	Yang	Proposed	Yang	Proposed
Traffic	0.25	1.66	-0.023	-0.071	50.75	67.38
PeopleOnStreet	0.24	1.73	-0.030	-0.078	42.63	69.25
Kimono	0.41	0.95	-0.028	-0.033	51.28	70.94
ParkScene	0.02	1.44	-0.001	-0.044	47.00	69.94
BasketballDrill	0.07	0.96	-0.006	-0.039	52.96	70.06
BQMall	0.54	1.25	-0.047	-0.053	49.08	72.94
PartyScene	0.28	1.72	-0.026	-0.078	28.69	70.38
RaceHorses	0.27	1.87	-0.032	-0.085	41.06	70.50
BQSquare	0.30	1.34	-0.017	-0.056	39.08	68.31
BlowingBubbles	0.19	1.79	-0.029	-0.082	33.84	71.19
Average	0.26	1.47	-0.024	-0.061	43.64	70.09

Table 5.The performance comparisons between Yang's and the proposed method as MRF=8.

	BD-rate(%)		BD-PSNRY(dB)		TIR (%)	
Sequence	Yang	Proposed	Yang	Proposed	Yang	Proposed
Traffic	0.24	1.41	-0.020	-0.062	70.25	77.38
PeopleOnStreet	0.22	1.43	-0.026	-0.065	66.13	77.63
Kimono	0.38	0.50	-0.023	-0.019	70.13	83.22
ParkScene	0.02	1.03	-0.001	-0.031	68.51	83.03
BasketballDrill	0.06	1.09	-0.005	-0.034	71.22	83.72
BQMall	0.49	1.27	-0.036	-0.053	69.67	85.78
PartyScene	0.25	1.45	-0.023	-0.066	59.88	83.50
RaceHorses	0.26	1.69	-0.021	-0.074	65.25	83.19
BQSquare	0.26	1.12	-0.019	-0.047	64.36	83.09
BlowingBubbles	0.17	1.68	-0.024	-0.072	61.65	84.38
Average	0.24	1.26	-0.020	-0.052	66.70	82.49

V CONCLUSION

In this paper, we propose a fast multiple reference frame selection method in MRF-ME using data mining technique to speed up the encoding process of H.265/HEVC. We employs AMVP algorithm to design the best MV predictor and select the best reference frame using data mining according to those decision trees which have been established in the MRF-ME module. The experimental results indicated the proposed fast MRF-ME algorithm based on data mining can effectively reduce encoding complexity at a negligible cost in terms of BD-rate and BD-PSNRY.

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