A New Fast Intra Prediction Algorithm for Spatial SHVC

Abstract: Since the Spatial Scalable High Efficiency Video Coding (SSHVC) can be adaptive to various terminal devices with different resolutions, it has a very promising potential. However, its coding process is very complex, which significantly restricts its wide applications. Therefore, it is very important to improve the coding speed. In this paper, we have proposed a new fast Intra prediction algorithm for SSHVC. Firstly, based on the observation that most CUs use ILR mode and its prediction process is very simple, we divide residual coefficients of ILR mode into two parts, and then use Z-test to determine the two parts do not use the same expected values and variances so as to early skip the current CU coding. Secondly, we found that RD costs between ILR mode and Intra mode are significantly different, and both RD costs of ILR mode and Intra mode follow the Gaussian distribution. Based on this feature, we propose to adopt GMM-EM to determine the best mode. Thirdly, when CUs use Intra mode to check, most of them select DM 0, 1, horizontal DMs and vertical DMs, while other DMs are very small but nonnegligible probability. We can predict candidate DMs based on their HCs, and use variable steps to search the best DM. Experimental results demonstrate that the proposed algorithm can significantly improve the coding speed with negligible coding efficiency losses.

Index Terms—SHVC, depth early skip, ILR mode, depth early termination.

I. INTRODUCTION

VIDEO applications, such as digital TV broadcasting, video conferencing, wireless video streaming, and smart phone communications, are more and more widely used in daily life. At the same time, more and more different terminal devices emerge. These terminal devices may have different screen resolutions. This requires that video streaming must be adaptive to different screen resolutions. Scalable High Efficiency Video Coding (SHVC) is an efficient solution to this requirement. SHVC consists of a base layer (BL) and one or more Enhancement layers (ELs). In order to adaptive to different screen resolutions, spatial SHVC (SSHVC) encodes different layers with different screen resolutions sequences, as shown in Fig. 1. Through selecting an appropriate layer, SSHVC can adapt to various devices with different screen resolutions.

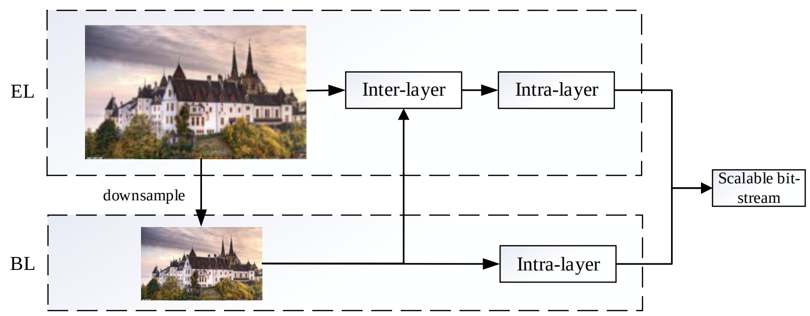


Fig. 1. BL and EL in SHVC

SSHVC consists of a BL and one and more ELs. A BL only consists of intra-layer prediction, while a EL further consist of inter-layer prediction. The coding process of intra-layer prediction is the same as that of HEVC. Since the contents between BL and EL are the same but their resolutions are different, BL needs to be unsampled to predict EL, which is inter-layer prediction. The corresponding mode is denoted as inter-layer reference (ILR) mode. Since the coding process of HEVC is already very complex, SSHVC needs to encode all its layers, it certainly has even more complex coding process, which will restrict its wide application, especially for wireless and real-time applications. Therefore, it is very important to reduce encoding complexity and improve coding speed.

For this purpose, in this research, we have proposed a novel fast intra prediction algorithm for spatial SHVC. First, we observe that most coding units (CUs) select ILR mode and its prediction process is very simple, then we directly test its residual coefficients to determine whether to skip the current depth. Second, we also observe the rate distortion (RD) costs between ILR mode and Intra mode have significant difference, and RD costs of both the two modes follow Gauss distribution, then we adopt Gaussian Mixture Model and Expectation Maximization (GMM-EM) to determine the best mode. Third, we also observe when CUs use Intra mode to check, most of them select directional mode (DM) 0, 1, horizontal DMs and vertical DMs, while other DMs are very small but nonnegligible probability. We can predict candidate DMs based on the Hadamard transform-based costs (HCs) in those DMs, and use variable steps to search the best DM in the other DMs.

The major novelties and contributions of the proposed algorithm are summarized below:

(1) Most CUs use ILR mode and its prediction is very simple, we directly determine whether to skip the current depth based on the residual coefficients of ILR mode.
(2) RD costs between ILR mode and Intra mode are significantly different, and both RD costs of both the two modes follow Gaussian distribution. Based on this feature, we use GMM-EM to determine the best mode.
(3) When CUs use Intra mode to check, most of them select DM 0, 1, horizontal DMs and vertical DMs, while other DMs are very small but nonnegligible probability. Based on their HCs, we can predict candidate DMs, and use variable steps to search the best DM.

II. RELATED WORK

In SHVC, each frame is divided into multiple Coding Tree Units (CTUs). Each CTU divide four depths by quad-tree partition, corresponding to sizes of a CU from 64×64 to 8×8. Each CU needs to check ILR mode and Intra mode. In order to improve the coding speed, the related works are reviewed as follows.

In order to avoid checking unnecessary coding depths to improve coding speed, we usually early skip or early terminate unlikely coding depths. In order to, using textual features and correlations to early skip unlikely coding depths are common methods. The work in [1] use a statistical method to study textural complexity and Quantizer Parameters (QPs) to predict candidate depths. Through a machine leaning approach, Liu et al. [2] use investigate textural features to predict likelihood depths and skip unlikely depths. Xu et al. [3] use deep learning to obtain textural features and decide whether or not to check the current depth for coding speedup. Theses above algorithms are predicted based on textural features only. In addition to textural features, correlations are also effective in prediction. In [4], according to spatial and inter-layer correlations, a Naïve Bayesian Classifier is adopted to predict the quad-tree structure of coding tree units (CTUs) for SHVC. Based on the coding information of relative CUs, a method about online-learning-based mode prediction is developed in [5] to predict the likelihood modes of the current CU in EL. As we know, HEVC has no inter-layer correlation but SHVC has inter-layer correlation. Therefore, fast coding algorithms for HEVC cannot use inter-layer correlation in prediction. If these algorithms are used straightforwardly in coding speedup for SHVC, they certainly cannot obtain the optimum performance. Therefore, it is crucial to develop fast coding algorithms for SHVC based on its own coding structure. Wang et al. [6-9] exploit both correlations and correlation degrees to predict candidate depths, and then use residual coefficients and RD costs to early terminate mode and depth selection. Based on interlayer, spatiotemporal correlations and inter-level correlations, the research [10] develops a conditional probability of a SKIP/Merge mode, motion activity and mode complexity to predict candidate modes. The inter-layer and spatiotemporal correlation are adopted in [11] to build two feedforwards neural network-based learning models to predict depths and modes. Theses above algorithms are predicted based on correlation only. Since both textural features and correlations are influence depth selection, jointly using them is also a common way in prediction. Lu et al. [12] use inter-layer and spatial correlations as well as textural complexity to predict candidate coding depths. Lu et al. [13][14] jointly use texture complexity and spatial-temporal correlation to predict candidate depths, and then combine inter-layer correlation with temporal correlation to exclude unlikely DMs.

In order to skip unlikely coding modes to improve coding speed, correlations and residual coefficients are usually used in prediction. Tohidypour et al. [15] use relative CUs' RD to predict the current CU's RD cost in EL for early termination. To reduce the coding complexity, the research proposed in [16] uses relative CUs to predict likelihood modes and skip unlikely modes in EL. According to the combination of depth and mode of the co-located CU in BL, the algorithm proposed in [17] first predicts likelihood modes and excludes unlikely modes of the current CU in EL, and then further eliminates unlikely modes based on inter-layer and spatial correlations. Wang et al. [7-8] first check ILR mode and merge mode, if their RD costs are very similar, it means they very likely to be the best mode, so checking other modes can be early terminated. Theses above algorithms are predicted based on correlation. Generally speaking, if a mode is predicted very well, its residual coefficients will obey Gaussian distribution [18] or Laplacian distribution [19]. Wang et al. [6] first check ILR mode, and then determine whether its residual coefficients follow Gaussian distribution so as to early skip Intra mode. Similarly, if a mode is predicted very well, its residual coefficients should be very small. Wang et al. [9] also first check ILR mode, and calculate its part-zero block based on the distribution of its residual coefficients to early terminate mode selection to improve the coding speed. Pan et al. [20] combine depth correlation and all-zero block to early terminate mode selection.

Intra prediction is a very time-consuming encoding process, developing DM selection algorithms is very important to improve the coding speed. Zhao et al. [21] use Sobel operator to calculate more likely DMs and skip unlikely DMs to improve the coding speed. Zhang et al. [22] obtain average gradients in the horizontal (AGH) and vertical directions (AGV), and then calculate the values of AGH/AGV to predict likely DMs. Based on improved edge detection, neighboring blocks and the sum of absolute Hadamard transformed difference (SATD) costs, the work [23] predicts candidate

DMs and skip some DMs to improve the coding speed. Yan et al. [24] merge adjacent modes into same groups, and then use early termination and pixel-based edge detection methods to further reduce the DMs. Zhang et al. [25] uses Hadamard cost-based progressive rough mode search to check likely DMs, so as to skip unlikely DMs to improve the coding speed. Wang et al. [6] combine relative CUs with the relationship between DMs and their corresponding HC values to predict candidate DMs and skip low likelihood modes. Wang et al. [9] combine textural features with the relationship between DMs and their corresponding HC values to predict candidate DMs and skip low likelihood modes. Jamali et al. [26] develop an RDO cost statistical modeling, and then predict likely DMs based on HCs and the modeling.

Although the above algorithms can improve the coding speed to some extent, there still exist some issues needs to be addressed for spatial SHVC:

(1) Textural features and correlation degrees are usually used to predict candidate depths. However, they are indirectly with depth selection. Therefore, using them only to predict depth selection cannot always obtain optimal performance.

(2) The principle behind mode selection between ILR mode and intra mode is not investigated. Residual coefficients are usually used to early terminate mode selection to improve the coding speed. Since the principle behind is not investigated, only using residual coefficients to early terminate mode selection cannot obtain the optimal performance.

(3) When CUs use Intra mode to check, the distribution of their corresponding DMs have not been investigated. Predicting candidate DMs without considering their distributions will certainly influence the performance improvements.

In order to address the above issues, we proposed a novel fast Intra prediction algorithm for spatial SHVC. We directly use residual coefficients of ILR mode to determine whether to skip the current depth, and then use GMM-EM to select the best mode between ILR mode and intra mode based on RD costs, finally we predict the candidate DMs based on their distribution.

III. Overview of the Proposed Algorithm

In order to improve Intra coding speed and maintain coding efficiency for spatial SHVC, we have proposed four strategies: Residual Coefficients of ILR Mode-Based Depth Early Skip (RCIM-BDES), RD Cost of ILR Mode-Based Mode Selection (RCIM-BMS), DM Distribution-Based DM Selection (DD-BDS), and Residual Coefficients of Depth-Based Depth Early Termination (RCD-BDET). The overview of the proposed algorithm is summarized in Fig. 1. First, we can early skip unlikely depths through RCIM-BDES. For the selected current depth candidates, we use RCIM-BMS to determine whether ILR mode is the best mode. In the affirmative, we can directly skip Intra prediction. Otherwise, we use DD-BDS to predict candidate DMs. After the depth has been checked, we use RC-BDET to determine whether it can be early terminated. The four strategies are showed in the left side of Fig.2, and the procedure of the proposed algorithm is presented in the right side.

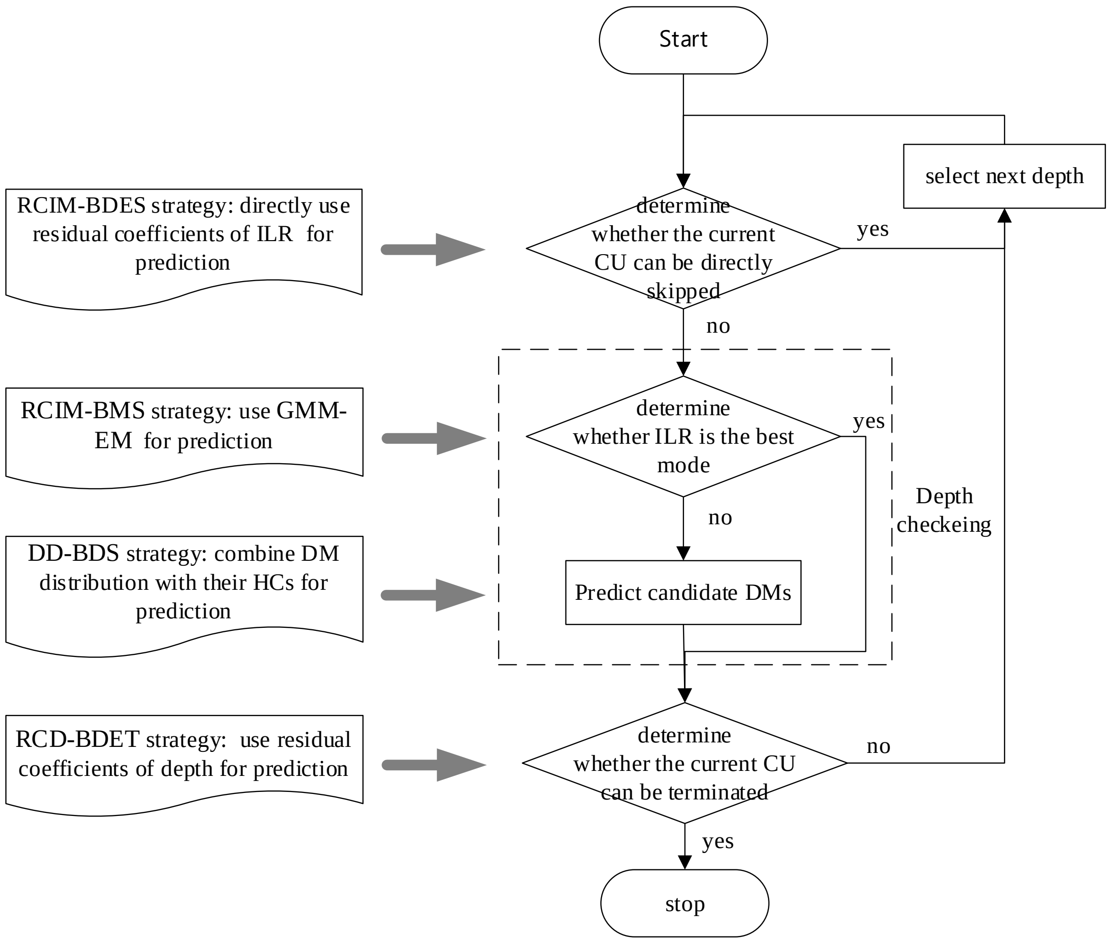


Fig. 2. Overview of the Proposed Algorithm.

IV. THE PROPOSED FAST INTRA PREDICTION PROCESS

In order to improve the coding speed, we have conducted extensive experiments to investigate of Intra coding in spatial SHVC. In order to ensure generality of the features and rules, different sequences, including motion and texture from simple to complex, are selected. In this research, we use Blue-sky, Ducks, Park_Joy, Pedestrian, Tractor, Town and Station2 in testing. According to common SHM test conditions (CSTC) [27], there exist scalability ratio 2x and 1.5x in spatial SHVC. In 2x, ratio of both height and width in EL to those in BL is 2; in 1.5x, ratio of both height and width in EL to those in BL is 1.5. Each scalability ratio also includes one set QP in BL and two set QP setting in EL: the QPs in the BL are (22, 26, 30, 34), and the corresponding QPs in the EL are (22, 26, 30, 34) and (24, 28, 32, 36), respectively. Since there are two scalability ratios, and each ratio includes two QPs, there are four sets of scalability ratios and QPs. Among the four sets of scalability ratio and QPs, 2x and QPs (24, 28, 32, 36) in EL should have the weakest inter-layer correlation. If it can achieve good performance, the other QPs set can obtain even better performances. Therefore, we only use 2x and QPs (24, 28, 32, 36) in EL in conducting experiments. Based on these experiments, we propose the corresponding fast Intra prediction strategies below.

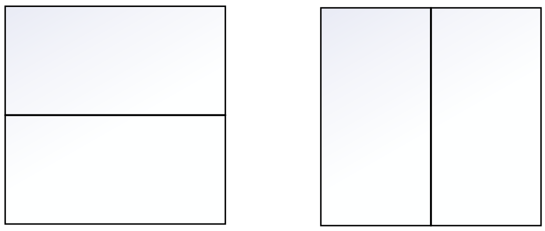
A. Residual Coefficients of ILR Mode-Based Depth Early Skip (RCIM-BDES)

In SHVC, each CTU includes four depths, corresponding to sizes of a CU from 64×64 to 8×8. Each CU needs to check both ILR mode and Intra mode, and then select the mode with the smaller rate distortion (RD) cost as the best mode. In order to investigate mode distribution between ILR mode and Intra mode, we use the aforementioned condition in testing. The corresponding mode distribution between ILR mode and Intra mode is listed in Table I.

Table I mode distribution between ILR mode and Intra mode

Sequence	ILR	Intra
Blue-sky	98.50%	1.50%
Ducks	99.76%	0.24%
Park_Joy	99.07%	0.93%
Pedestrian	90.65%	9.35%
Tractor	97.68%	2.32%
Town	96.84%	3.16%
Station2	95.27%	4.73%
Average	96.82%	3.18%

From Table I, we can find that the average percentage of ILR mode is 96.82%. In other words, most CUs select ILR mode as the best mode. The reason is that the content in BL and EL are the same, and QPs in BL and EL are similar or even the same, the inter-layer correlation is very strong. In addition, the prediction of ILR mode is obtained directly by upsampling the co-located CUs in BL, so the process is very simple. Therefore, we can first obtain the residual coefficients of ILR mode without encoding it, and determine whether the current CU needs to be further split based on the residual coefficients. In the affirmative, the current CU can be directly skipped. Otherwise, we need to further encode ILR mode and Intra mode.



(a) Top and bottom (b) Left and right

Fig.3. The division of the CU.

We first divide the CU of the residual coefficients into top and bottom parts as shown in in Fig. 3 (a) and left and right parts as shown in in Fig. 3 (b). Obviously, if two parts of any division are significantly different, it means that the current CU needs to be further split. In general, if a CU is predicted very well by the best mode, the corresponding residual coefficients will follow Gauss distribution [18]. Suppose the residual coefficients obey a Gaussian distribution, the residual coefficients of one part in each division are respectively modeled as:

$$X \sim N\left(\mu_1, \sigma_1^2\right) \tag{1}$$

where X is the residual coefficients of the part, μ_1 and σ_1^2 are respectively its expected value and variance. Suppose $x_1, x_2, \cdots, x_n$ are samples in X, the μ_1 and σ_1^2 can be derived by maximum likelihood estimation (MLE). The probability density function of X is:

$$f\left(x;\mu_1,\sigma_1^2\right)=\frac{1}{\sqrt{2\pi}\sigma_1}\exp\left[-\frac{1}{2\sigma_1^2}\left(x-\mu_1\right)^2\right], \tag{2}$$

its corresponding likelihood function is:

$$L\left(\mu_1,\sigma_1^2\right)=\prod_{i=1}^{n}\frac{1}{\sqrt{2\pi}\sigma_1}\exp\left[-\frac{1}{2\sigma_1^2}\left(x_i-\mu_1\right)^2\right]=\left(2\pi\right)^{-n/2}\left(\sigma_1^2\right)^{-n/2}\exp\left[-\frac{1}{2\sigma_1^2}\left(x_i-\mu_1\right)^2\right], \tag{3}$$

$$InL\left(\mu_1,\sigma_1^2\right)=-\frac{n}{2}In\left(2\pi\right)-\frac{n}{2}In\left(\sigma_1^2\right)-\frac{1}{2\sigma_1^2}\left(x_i-\mu_1\right)^2 , \tag{4}$$

where n is the number of residual coefficients in each part. In order to obtain μ_1 and σ_1^2, we can calculate below:

$$\begin{cases}\dfrac{\partial InL}{\partial\mu_1}=\dfrac{1}{\sigma_1^2}\left(\sum_{i=1}^{n}x_i-n\mu_1\right)=0\\ \dfrac{\partial InL}{\partial\sigma_1^2}=-\dfrac{n}{2\sigma_1^2}+\dfrac{1}{2\left(\sigma_1^2\right)^2}\sum_{i=1}^{n}\left(x_i-\mu_1\right)^2=0\end{cases} \tag{5}$$

From Equ. (5), we can derive μ_1 and σ_1^2 can be obtained and they are:

$$\mu_1=\frac{1}{n}\sum_{i=1}^{n}x_i,\ \sigma_1^2=\frac{1}{n}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2 \tag{6}$$

Through the above process, we can obtain μ_1 and σ_1^2 of one part, and then we use them to test whether the residual coefficients of the other part also use them. Suppose Y is the residual coefficients of the other part, $y_1,y_2,\ldots,y_n$ are its samples. We can test whether Y also use μ_1 and σ_1^2 as follows:

$$\left|\frac{\bar{Y}\text{-}\mu_1}{\sigma_1/\sqrt{n}}\right|>s_\alpha , \tag{7}$$

where α is the significance level value. For any α, the corresponding threshold value s_α can be obtained by checking Gaussian distribution table. If (7) is satisfied, the residual coefficients of the two parts do not use the same expected value and variance. Therefore, the two parts are significantly different, the current CU needs not to be checked and be skipped directly.

Since different depths may have different probability to be skipped, so we need to select the best threshold value of every depth. For depth 2, we select some common values to check, their corresponding coding efficiencies are relatively large. In order to improve coding efficiency, we select the largest values 3.49 in Gaussian distribution table, and further use its multiples in testing, the corresponding coding efficiency are listed in Table 2.

Table 2. coding efficiency under different test values

Test values / Sequence	3.49	6.98	10.47	13.96	17.45	20.94	24.43	27.92
blue_sky	0.36%	0.40%	0.38%	0.27%	0.15%	0.10%	0.04%	0.04%
ducks	0.10%	0.09%	0.08%	0.03%	0.01%	0.00%	0.00%	0.00%

park_joy	0.43%	0.34%	0.20%	0.09%	0.04%	0.01%	0.01%	0.00%
pedestrian	0.17%	0.25%	0.23%	0.17%	0.18%	0.09%	0.04%	0.00%
town	0.32%	0.29%	0.23%	0.12%	0.04%	0.02%	0.01%	0.00%
station2	0.00%	0.07%	0.12%	0.08%	0.04%	0.05%	0.02%	0.01%
tractor	0.13%	0.14%	0.13%	0.10%	0.04%	0.02%	0.00%	-0.01%
Average	0.22%	0.23%	0.20%	0.12%	0.07%	0.04%	0.02%	0.01%

In Table 2, coding efficiency are denoted by BDBR [28], which measures the bitrate difference at equal PSNR in the EL. A positive or negative BDBR reflects a coding efficiency loss or increase, respectively. We can observe that when test value is greater than or equal to 20.94, BDBRs in all sequences are less than 0.1%. Therefore, test value 20.94 is selected as threshold value in depth 2. In the similar way, we obtain threshold values for depth 1 is 31.41. If we skip depth 0, the corresponding coding efficiencies will degrade obviously in some sequences. Therefore, we do not skip depth 0. Based on the above analysis, we can rewrite the depth skip conditions as follows:

$$s_{\alpha} = \begin{cases} 31.41 & \text{depth 1} \\ 20.94 & \text{depth 2} \end{cases}, \tag{8}$$

When the above condition is satisfied, we can directly skip the corresponding depth.

B. RD Cost of ILR Mode-Based Mode Selection (RCIM-BMS)

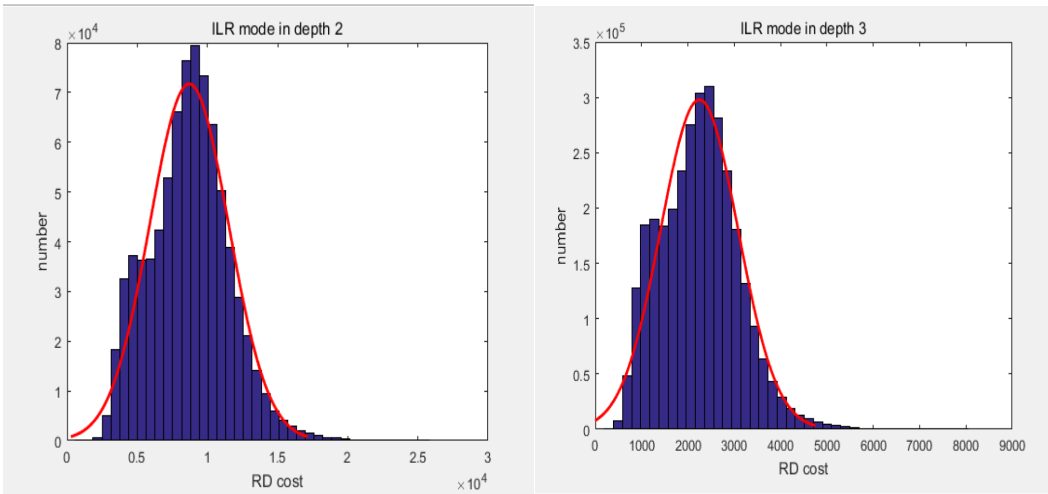
As mentioned above, ILR mode occupies the majority of mode distribution. However, in some sequences, Intra mode also occupies nonnegligible proportion, such as sequence "Pedestrian". If we only use ILR mode to check, the corresponding coding efficiency may be obviously degraded in some sequence. However, if we use both ILR mode and Intra mode to check, much unnecessary coding time would be costed in many sequences. In order to improve the coding speed and maintain the coding efficiency, we need to investigate mode selection principle behind. Using the aforementioned condition in testing, we can obtain RD Costs of ILR mode and Intra mode, which are list in Table 3.

Table 3. RD Cost of ILR mode and Intra mode

Sequence	Depth 0		Depth 1		Depth 2		Depth 3	
	ILR	Intra	ILR	Intra	ILR	Intra	ILR	Intra
Blue-sky	49801	11074	12172	3198	3039	1523	778	946
Ducks	140109	49873	34478	13686	8701	5732	2247	2444
Park_Joy	166607	21382	41191	5616	10308	3066	1888	2621
Pedestrian	37458	26252	9333	7063	2351	2189	609	763
Tractor	57344	22816	14445	5734	3719	2433	988	1189
town	108752	63737	27495	16467	6875	4908	1721	1981
station2	44750	12625	11201	4611	2839	2300	742	901
average	86403	29680	21474	8054	5405	3164	1282	1549

From Table 3, we can observe that RD Cost of ILR mode is significantly larger than that of Intra mode from depth 0 to 2; while RD Cost of ILR mode is smaller than that of Intra mode in depth 3. The reason is ILR and Intra mode use different processes in prediction. ILR mode use co-located pixels in BL to upsample in horizontal and vertical directions. Intra mode uses 35 directional modes in prediction. For large CUs, namely depth from 0 to 2, reference pixels and pixels in the current CU correlation is not very strong. If texture is very complex, co-located pixels in BL can predict the current CU better than reference pixels, so ILR mode is selected as the best mode. If texture is very simple, 35 directional modes can predict the current CU better than upsampling in horizontal and vertical directions, so Intra mode is selected as the best mode. For small CUs, namely depth 3, reference pixels and pixels in the current CU correlation is very strong. If texture is very complex, Intra mode with 35 DMs can predict the current CU better than ILR mode, so Intra mode is selected as the best mode. If texture is very simple, both ILR mode and Intra mode can predict very well, the difference of their RD cost is also very small, so either of them can be selected as the best mode. Therefore, the average difference of their RD cost is not very significantly.

In addition to the difference of RD Costs of ILR mode and Intra mode, we further investigate the RD cost distribution of ILR mode and Intra mode. In Fig.2, the horizontal axis represents RD costs, and the vertical axis represents the corresponding numbers. Fig.2. (a) and Fig.2. (b) shows that the RD cost distribution of ILR mode with sequence “Ducks” in depth 2 and depth 3, respectively.

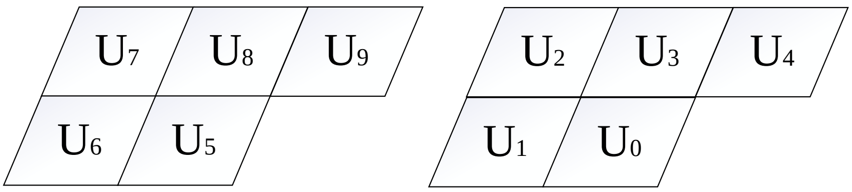


(a) (b)

Fig.4. The RD cost distribution of ILR with sequence “Ducks”

From Fig.4, we can observe that both the RD cost of ILR in depth 2 and depth 3 follow Gaussian distribution. Extensive experiments show that RD cost distribution of ILR mode and Intra mode in all sequences follow Gaussian distribution.

Based on the above analysis, we can draw a conclusion: RD Cost of ILR mode is different from that of Intra mode in all depths, and their distributions all follow Gaussian distribution. Based on this feature, we propose to adopt Gaussian Mixture Model and Expectation Maximization (GMM-EM) to determine the best mode. Since ILR mode occupies the majority of mode distribution, we can encode ILR mode, and then use GMM-EM to determine whether ILR mode is the best mode based on its RD cost. In the affirmative, we can directly skip Intra mode; otherwise, we need to further check Intra mode.



(a) previous frame (b) the current frame

Fig.5. The current CU and its Relative CUs

In order to use GMM-EM in prediction, we use coding information modes and RD costs of relative CUs of the current CU in prediction. As shown in Fig.5, U_0 is the current CU, U_1, U_2, U_3 and U_4 are the neighboring of the current CU, U_5, U_6, U_7, U_8 and U_9 are the co-located CUs of U_0, U_1, U_2, U_3 and U_4. For any U_i, its corresponding RD cost is denoted as rd_i. The corresponding Gaussian Mixture Model is:

$$p(rd_i \mid \pi, \mu, \Sigma) = \pi_1 N(rd_i \mid \mu_1, \Sigma_1) + \pi_2 N(rd_i \mid \mu_2, \Sigma_2), \tag{9}$$

where π_1 is the possibility of using ILR mode, μ_1 and Σ_1 are respectively expected value and variance of their RD cost; and π_2 is the possibility of using Intra mode, μ_2 and Σ_2 are respectively expected value and variance of their RD cost. M is the number of the current CU and its relative CUs, and it is 10.

In order to obtain these six parameter values, the maximum likelihood estimation is used in calculation as follows:

$$f = \prod_{i=1}^{M} p(rd_i \mid \pi, \mu, \Sigma) = \prod_{i=1}^{M} \left(\pi_1 N(rd_i \mid \mu_1, \Sigma_1) + \pi_2 N(rd_i \mid \mu_2, \Sigma_2)\right) \tag{10}$$

The logarithm of the likelihood function is:

$$\log(f) = \sum_{i=1}^{M} \log\left(\pi_1 N(rd_i \mid \mu_1, \Sigma_1) + \pi_2 N(rd_i \mid \mu_2, \Sigma_2)\right) \tag{11}$$

π_k, μ_k, Σ_k can been calculated by:

$$\frac{\partial \log(f)}{\partial \pi_k} = 0, \quad \frac{\partial \log(f)}{\partial \mu_k} = 0, \quad \frac{\partial \log(f)}{\partial \Sigma_k} = 0 \qquad k = 1 \text{ or } 2 \tag{12}$$

We can derive:

$$\mu_k = \frac{1}{N_k} \sum_{i=1}^{N} \gamma(i,k) x_i, \ \Sigma_k = \frac{1}{N_k} \sum_{i=1}^{N} \gamma(i,k)(x_i - \mu_k)(x_i - \mu_k)^T \tag{13}$$

where $N_k = \sum_{i=1}^{N} \gamma(i,k)$, then we have:

$$\pi_k = \frac{N_k}{N} \tag{14}$$

$\gamma(i,k)$ is the probability that rd_i is generated by the *k-th* part, and it can be obtained by:

$$\gamma(i,k) = \frac{\pi_k N(x_i \mid \mu_k, \Sigma_k)}{\pi_1 N(x_i \mid \mu_1, \Sigma_1) + \pi_2 N(x_i \mid \mu_2, \Sigma_2)} \tag{15}$$

Repeat iterations (13), (14) and (15) until $\gamma(i,k)$ converges.

Since the current CU is U_0, in order to decide whether ILR mode is the best mode, we need to determine if $\gamma(0,k)$ converges. Suppose the i-th iteration of $\gamma(0,k)$ is denoted as $\gamma_i(0,k)$. In order to avoid unnecessary repeat iterations, if the absolute difference between $\gamma_{i\text{-}1}(0,k)$ and $\gamma_i(0,k)$ is very small, we can terminate the repeat iteration. We can empirically select 0.01 as a threshold, then we have:

$$\left|\gamma_i(0,k) - \gamma_{i-1}(0,k)\right| \le 0.01. \tag{16}$$

If condition (16) is met, we can terminate the repeat iteration. Through the above process, we can obtain the possibility of the current CU selecting ILR mode. Since this possibility is obtained based on *RD* cost, we define it as *RD* based probability.

Since relative CUs are usually very similar, we can use relative CUs in prediction. Obviously, if more relative CUs use ILR mode, the current CU is more likely to use this mode, vice versa. In other words, the probability of current CU selecting ILR mode is proportional to the number of relative CUs using ILR mode. As shown in Fig.3, the current CU has nine relative CUs. Therefore, the possibility of the current CU selecting ILR mode can be written as $\frac{k}{9}$, where k is the number of relative CUs using ILR mode. Since this possibility is obtained based on the number of relative CUs using ILR mode, we define it as number-based probability.

Since both *RD* based probability and number-based probability have strong relationship with the ILR mode selection, we can combine with them to predict the probability to use ILR mode. Let A and B denote the *RD* based probability and the number-based probability, respectively. Obviously, both of them are independent, we can derive:

$$p_r = p\left(A+B\right) = p(A) + p(B) - p(A)p(B) \tag{17}$$

where p_r denotes the possibility of depth early termination. If p_r is greater than or equal to 0.6, the current CU is very likely to be early terminated. Therefore, we use 0.6, 0.7, 0.8 and 0.9 during testing, and the corresponding BDBRs are presented in Table 4.

Table 4. The possibility of depth early termination p_r and the corresponding BDBRs

Pr & BDBR	0.6	0.7	0.8	0.9
Blue-sky	-0.3%	-0.3%	-0.3%	-0.3%
Ducks	0.0%	0.0%	0.0%	0.0%
Park_Joy	0.0%	0.0%	0.0%	0.0%
Pedestrian	-0.1%	-0.1%	-0.1%	-0.1%
Tractor	-0.1%	0.0%	0.0%	0.0%
town	-0.1%	-0.1%	-0.1%	-0.1%
station2	0.0%	-0.1%	-0.1%	-0.2%

From Table 4, we can find that BDBR stays the same except in sequence "station2" under different p_r. When p_r is equal to 0.9, BDBR achieve the smallest value in sequence "station2". Therefore, we select 0.9 as the best value for p_r.

C. DM Distribution-Based DM Selection (DD-BDS)

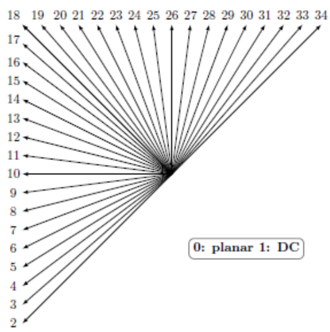


Fig.6. 35 DMs in SHVC

Similar to HEVC, SHVC also use 35 DMs in prediction, as shown in Fig.6. Through checking the 35 DMs, the DM with the smallest HC can be obtained which is defined as the best DM. As mentioned in the above section, for large CUs, simple CUs usually use Intra mode; for small CUs, complex CUs usually use Intra mode. In order to obtain their DM distributions, we use the aforementioned condition in testing. The corresponding DM distributions in large CUs and small CUs are list in Table 5.

Table 5. DM distribution in large CUs and small CUs

Sequence	Large CU		Small CU	
	0	1	0	3
Blue-sky	68.23%	82.38%	76.41%	83.93%
Ducks	20.28%	90.78%	30.37%	85.39%
Park_Joy	66.55%	83.84%	67.70%	82.39%
Pedestrian	57.92%	93.08%	69.89%	94.62%
Tractor	38.31%	73.00%	52.58%	81.85%
Town	72.85%	94.80%	61.73%	92.59%
Station2	41.27%	70.45%	54.74%	74.32%
Average	52.20%	84.05%	59.06%	85.01%

In Table 5, 0 and 1 refer to class 0 and 1. Class 0 refers to DM 0 and 1, Class 1 refers to DM 0, 1, 8, 9, 10, 11, 12, 24, 25, 26, 27 and 28. From Table 6, we can find that more than 50% CUs use class 0, 85% CUs use class 1. The reason is as follows: if large CUs use Intra mode, they are usually very simple, so the distribution of their DMs is very regularly; while for small CUs, their sizes are very small so their texture cannot change very significantly, so the distribution of their DMs also are very regularly. Since class 1 occupies about 85%, the other DMs occupy about 15%. We define the other DMs as class 2.

Although class 0 only includes 2 DMs, it occupies more than 50% possibility. If we can determine the best DM in class 0, we can significantly improve the coding speed. Similarly, class 1 includes 12 DMs, it occupies about 85% possibility. It means that the best DM is very likely in class 1. If HC of a DM is smaller than those of its neighboring two DMs, we define the DM as local minim DM(LMD). The best DM should be identified within LMDs. After checking class 1, if there is a LMD, it is very likely to be the best DM, so we can early terminate DM selection. Otherwise, we need to further check class 2. Since the probability of class 2 is very small but cannot totally ignored. If we always check all the DMs, it will cost much unnecessary time. However, if we directly skip these DMs, the coding efficiency will be obviously degraded. Therefore, we use variable step and binary search to obtain the best DMs. For the convenience of later description, we define C_i as the HC of DM i . Based on the above analysis, we propose the corresponding method to predict the candidate DMs as follows:

(1) We first select DM 0, 1, 10 and 26 to check. The smaller HC in DM 0 and 1 is denoted as min (0, 1), the smaller HC in DM 10 and 26 is denoted as min (10, 26). If min (0, 1) is significantly smaller than min (10, 26), DM 0 and 1 are very likely to be the best DM, go to (10); else go to (2).

(2) We compare C_{10} with C_{26} to further select likely DMs: if C_{10} is significantly smaller than C_{26} , go to (3); else if C_{26} is significantly smaller than C_{10} , go to (5); else go to (7).

(3) The best DM is very likely to in horizontal DMs. Since the best DM is very likely in class 1, we further check DM 8, 9, 11, 12. If there is a LMD within DM 9, 10 and 11, the DM is very likely to be the best DM, go to (10). Otherwise, go to (4).

(4) we further check DM 2, 6, 14 and 18. If the DM with the smallest HC is not within DM 2, 6, 8, 12, 14 or 18, the best DM has a very small probability in class 2, there is no need to further check other DMs in class 2, go to (10). Otherwise, binary search is used to obtain the best DMs, go to (9).
(5) The best DM is very likely to in vertical DMs. Since the best DM is very likely in class 1, we further check DM 24, 25, 27, 28. If there is a LMD within DM 25, 26 and 27, the DM is very likely to be the best DM, go to (10). Otherwise, go to (6).
(6) We further check DM 18, 22, 30 and 34. If the DM with the smallest HC is not within DM 18, 22, 24, 28, 30 and 34, the best DM has a very small probability in class 2, there is no need to further check other DMs in class 2, go to (10). Otherwise, binary search is used to obtain the best DMs, go to (9).
(7) Since the best DM is very likely in class 1 and DM 10 and 26 have already been checked, we further check class 2 except DM 10 and 26. If there is a LMD within DM 9, 10, 11, 25, 26 and 27, the DM is very likely to be the best DM, go to (10). Otherwise, go to (8).
(8) We further check DM 2, 6, 14, 18, 22, 30 and 34. If the DM with the smallest HC is not within DM 2, 6, 8, 12, 14, 18, 22, 24, 28, 30 and 34, there is no need to further check other DMs in class 2, go to (10). Otherwise, binary search is used to obtain the best DMs, go to (9).
(9) The best DM is very likely within class 2. We further check the middle of the DM with the smallest HC and its left (right) checked neighboring DMs and select the DM with the smallest HC, repeat the process until a DM is a LMD. The DM is very likely the best DM, go to (10).
(10) The DM selection is terminated.

In order to decide whether two DMs' HCs have significant difference, their corresponding residual coefficients are investigated. Suppose R_1 and R_2 are residuals of two DMs, their difference R is:

$$R = R_1 - R_2 \tag{18}$$

Through Hadamard transformation, the above equation can be rewritten as:

$$HRH = HR_1H - HR_2H \ , \tag{19}$$

where H is a $m \times m$ Hadamard matrix. According to Cauchy-inequality, we can derive:

$$HRH \le \left| \sum_{i=0}^{m} \sum_{j=0}^{m} \left(HH^T \right)^2 \right|^{\frac{1}{2}} \times \left| \sum_{i=0}^{m} \sum_{j=0}^{m} r^2 \left(i, j \right) \right|^{\frac{1}{2}} \le \sqrt{m} \left| \sum_{i=0}^{m} \sum_{j=0}^{m} r^2 \left(i, j \right) \right|^{\frac{1}{2}} \tag{20}$$

where m is the size of the current CU. Then

$$\sqrt{m} \left| \sum_{i=0}^{m} \sum_{j=0}^{m} r^2 \left(i, j \right) \right|^{\frac{1}{2}} \le \sqrt{m} \sum_{i=0}^{m} \sum_{j=0}^{m} \left| r \left(i, j \right) \right| \tag{21}$$

$x_{i,j}$ is a value in HRH at (i, j) position, which is calculated by:

$$x_{i,j} = \sum_{k=0}^{m} \sum_{p=0}^{m} h_{ik} r_{kp} h_{pj} \le \sum_{k=0}^{m} \sum_{p=0}^{m} \left| h_{ik} h_{pj} \right| \left| r_{kp} \right| \le \sum_{k=0}^{m} \sum_{p=0}^{m} \left| r_{kp} \right| \tag{22}$$

If any quantized values in HRH is smaller than k , R_1 and R_2 are not significantly different. The following condition should be satisfied:

$$\sum_{k=0}^{m} \sum_{p=0}^{m} \left| r_{kp} \right| < kQ_{step} \tag{23}$$

Combine Eq. (18), (19), (20), (23), we can derive:

$$\left| HR_1H - HR_2H \right| < k\sqrt{m}Q_{step} \tag{24}$$

Eq. (24) can be written as:

$$|HC_1 - HC_2| < k\sqrt{m}Q_{step}, \tag{25}$$

where HC_1 and HC_2 refers to Hadamard transform values of two IMs. If Eq. (25) is satisfied, we can consider that they are not significant different. Conversely, the significant different condition can be written as:

$$|HC_1 - HC_2| > k\sqrt{m}Q_{step}, \tag{26}$$

If Eq. (26) is satisfied, they can be considered to be significant different. In order to obtain the best k, we use the aforementioned condition in testing. The corresponding the corresponding BDBRs are list in Table 6.

Table 6. k and the corresponding BDBRs

	1	2	3	4	5	6
blue_sky	0.00%	0.00%	0.00%	0.01%	0.01%	0.00%
ducks	-0.01%	-0.01%	0.00%	-0.01%	0.00%	0.00%
park_joy	-0.01%	-0.03%	0.00%	0.00%	0.01%	0.01%
pedestrian	-0.02%	0.00%	0.00%	0.00%	0.00%	0.01%
town	-0.16%	-0.11%	-0.10%	-0.07%	-0.03%	-0.02%
station2	0.16%	0.14%	0.13%	0.11%	0.08%	0.06%
tractor	0.01%	0.00%	0.01%	0.00%	-0.01%	-0.01%

From Table 6, we can find that there is a turning point when k is equal to 5. If k greater than or equal to 5, the corresponding BDBRs in all sequences are small than 0.1%. It means that k with 5 can obtain very good performance. If we further select larger k, the corresponding coding speed improves will be smaller. Therefore, k is set to 5.

In order to describe conveniently, we use “<<” to represent significantly smaller than. The corresponding flowchart is shown in Fig.6.

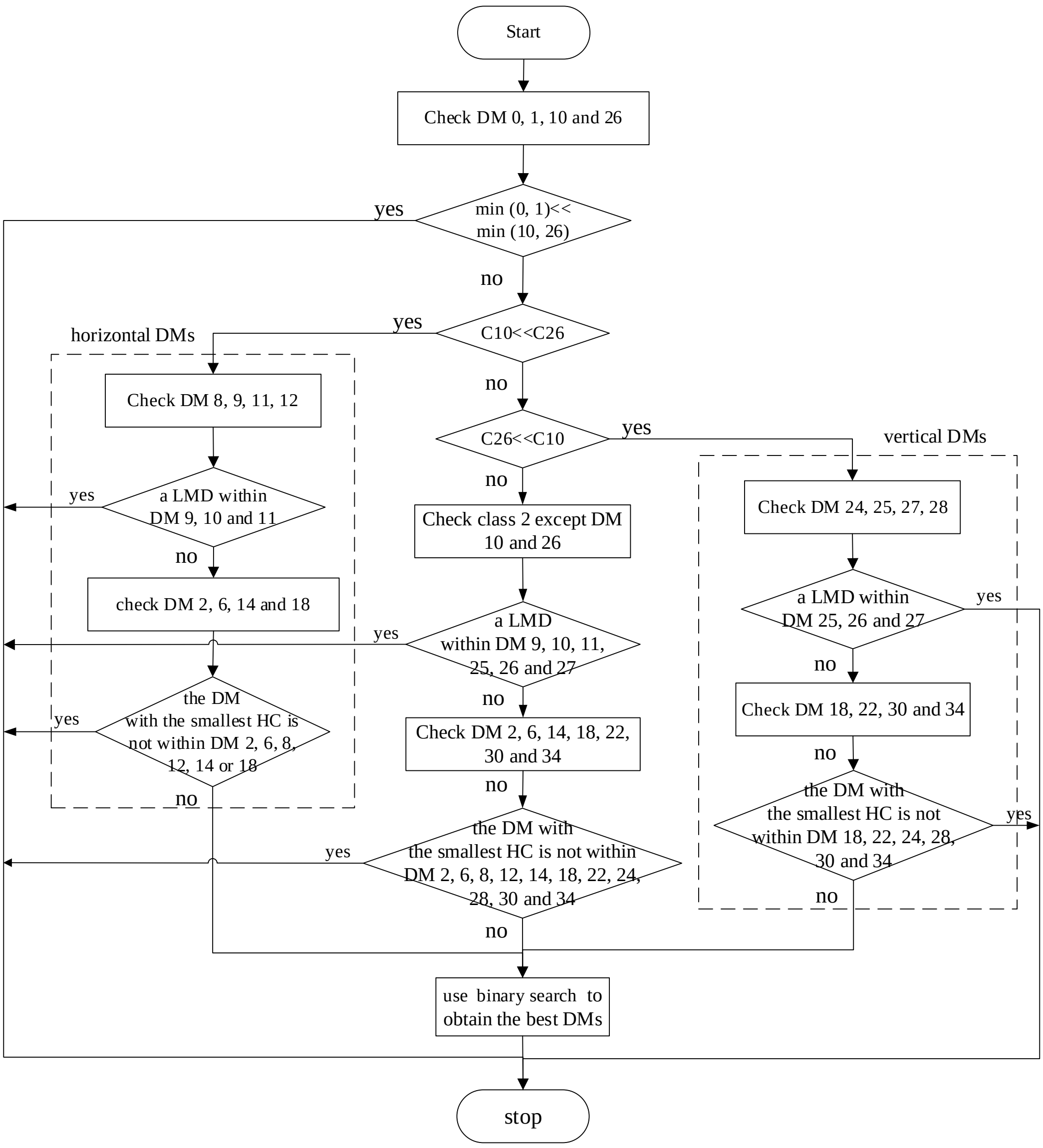


Fig.6. Flowchart of DM selection

D. Residual Coefficients of Depth-Based Depth Early Termination (RCD-BDET)

After the current CU has been checked, we can obtain its residual coefficients. Similar to depth skip, we also use two ways to divide the CU of the residual coefficients into two parts, as shown in Fig.3. If residual coefficients of two parts in each division do not have significant difference, the current depth is very likely to be the best depth. Therefore, the current CU needs not to be further split and depth selection can be early terminated. Also similar to depth skip, we first use MLE to calculate the μ_2 and σ_2^2 of one part, and then use them to test whether the other parts also use them. Suppose Z is the residual coefficients of the other part, $z_1, z_2, \cdots, z_n$ are its samples. We can test whether Z also use μ_2 and σ_2^2 as follows:

$$\left|\frac{\bar{Z}-\mu_2}{\sigma_2/\sqrt{n}}\right| < e_\alpha , \tag{27}$$

where α is the significance level value, n is the number of residual coefficients in each part. By checking Gaussian distribution table, we can obtain the corresponding threshold value e_α. If (7) is satisfied, the residual coefficients of the two parts use the same expected value and variance. Therefore, the two parts do not have significant difference, the current CU can be early terminated. We select some common α values to check, such as 0.0005, 0.0015, 0.0025, 0.0045, 0.0125, 0.015 and 0.025. The corresponding threshold value are 3.3, 2.96, 2.81, 2.61, 2.24, 2.17 and 1.96, respectively. Experiments shown their corresponding coding efficiency losses are relatively large. In order to improve, we first divide 1.96 by 2, and then divide the value by 2, repeat the process until coding efficiency losses are very small. Based on experiments, the corresponding thresholds for depth early termination are list below:

$$e_\alpha = \begin{cases} 0.1225 & \text{depth 1} \\ 0.245 & \text{depth 2} \end{cases} \tag{28}$$

IV. Experimental Results

In order to verify the performance of the proposed fast Intra prediction algorithm for spatial SHVC, we use the reference software (SHM 11.0) and test the proposed algorithm on a server with Intel (R) 2.0 GHz CPU and 30 GB memory. The training and testing sequences have no overlaps to ensure the generality of our proposed algorithm. The performances of algorithms are evaluated by coding efficiency and coding speed. Coding efficiency includes bitrate and visual quality, which is indicated by BDBR. It refers to the bitrate difference at equal PSNR compared with the reference software in the EL. Coding speed is denoted by TS, which evaluates the percentage of encoding run-time savings only in the EL.

As mentioned above, we have proposed four strategies: RCIM-BDES, RCIM-BMS, DD-BDS, and RCD-BDET. Since both RCIM-BDES and RCD-BDET are developed for depth prediction, we merge them and denoted them as “Depth”. Using previously used parameter configuration, we also only use 2x and QPs (24, 28, 32, 36) in EL in testing. The corresponding coding performance is list in Table 7.

Table 7. Performance comparisons among different strategies

Sequence	Depth (%)		RCIM-BMS (%)		DD-BDS (%)	
	BDBR	TS	BDBR	TS	BDBR	TS
Traffic	0.09	43.52	-0.17	75.01	-0.02%	35.63
PeopleOnStreet	0.02	44.91	-0.30	75.33	0.00%	36.04
Kimono	-0.02	45.55	-0.30	74.23	-0.08%	36.77
ParkScene	0.05	43.41	-0.10	72.39	-0.02%	35.60
Cactus	0.21	43.86	0.30	68.64	0.28%	34.87
BasketballDrive	0.46	44.06	0.70	60.47	0.34%	34.68
BQTerrace	0.19	42.51	1.50	64.19	0.75%	34.62
Average	0.14	43.97	0.23	70.04	0.18	35.46

From Table 7, we can find that that the average coding speed improvements in “Depth”, “RCIM-BMS” and “Depth” are 43.97%, 70.04%, 35.46%, respectively. Their corresponding average coding efficiency losses are 0.14%, 0.23%, 0.18%, correspondingly. Obviously, all the three strategies can remarkably accelerate the coding speed with very small coding efficiency losses. Since the coding process of ILR is simple and most CUs only use the mode, GMM can improve the coding speed most significantly. Since the thresholds for early skip and early termination are very strict, "Depth" improve the coding speed not very significantly. Its coding efficiency losses are also very small. Since Intra prediction include RMD and RDO process, we only skip some unnecessary DMs in RMD, its coding speed improve least significantly.

In order to demonstrate the performance of the proposed algorithm which integrates all of the proposed strategies. The performance of our algorithm is compared with that of PAPS algorithm [4], EETBS algorithm [13] and FIICA algorithm [14]. To the best of our knowledge, these three algorithms are the best and most recent algorithms for spatial Intra SHVC. For fair comparisons, all algorithms are tested on the same computing platform. As mentioned above, due to two scalability ratios and two QPs settings, we classify their combinations into four cases in EL. Case 1 is scalability ratio 1.5x and the QP set (22, 26, 30, 34), case 2 is scalability ratio 1.5x and the QP set (24, 28, 32, 36), case 3 is scalability ratio 2x and the QP set (22, 26, 30, 34), and case 4 is scalability ratio 2x and QP set (24, 28, 32, 36). The overall performance comparisons in terms of coding efficiency and coding speed are listed in Table 8 (case 1), Table 9 (case 2), Table 10 (case 3) and Table 11 (case 4), respectively.

Table 8. Performance comparisons with case 1

Sequence	Proposed (%)		PAPS (%) [4]		EETBS(%) [13]		FIICA (%) [14]	
	BDBR	TS	BDBR	TS	BDBR	TS	BDBR	TS
Kimono	-0.37	80.81	0.06	70.81	0.41	71.43	-0.21	62.35
ParkScene	-0.14	79.75	0.49	66.50	0.01	62.86	-0.1	38.17
Cactus	0.00	79.80	0.10	65.37	-0.20	46.05	-0.21	41.89
BasketballDrive	0.30	78.08	0.46	67.14	0.50	48.48	0.42	47.06
BQTerrace	0.30	78.80	0.39	65.32	0.32	47.89	0.41	46.27
Average	0.02	79.45	0.30	67.03	0.21	55.34	0.06	47.15

Table 9. Performance comparisons with case 2

Sequence	Proposed (%)		PAPS (%) [4]		EETBS(%) [13]		FIICA (%) [14]	
	BDBR	TS	BDBR	TS	BDBR	TS	BDBR	TS
Kimono	-0.22	82.03	0.17	68.76	0.63	72.69	0.81	61.67
ParkScene	-0.10	81.37	0.58	67.43	-1.12	65.13	-1.2	37.46
Cactus	-0.24	81.41	0.27	63.21	0.41	45.83	0.32	40.13
BasketballDrive	-0.11	80.46	0.41	66.17	-1.00	49.32	-0.83	44.36
BQTerrace	0.04	80.38	0.48	63.68	0.10	48.53	0.01	45.15
Average	-0.13	81.13	0.38	65.85	-0.20	56.30	-0.18	45.75

Table 10. Performance comparisons with case 3

Sequence	Proposed (%)		PAPS (%) [4]		EETBS(%) [13]		FIICA (%) [14]	
	BDBR	TS	BDBR	TS	BDBR	TS	BDBR	TS
Traffic	0.10	78.00	0.24	76.40	0.30	53.12	0.39	36.37
PeopleOnStreet	0.51	78.20	0.22	62.80	0.02	51.91	0.10	39.43
Kimono	-0.13	78.45	0.21	73.12	-0.10	70.12	-0.14	60.27
ParkScene	-0.07	77.04	0.42	64.51	0.20	63.87	0.20	36.49
Cactus	1.25	75.18	0.58	70.67	0.80	45.63	0.91	37.92
BasketballDrive	1.69	70.42	1.87	67.42	0.81	47.59	0.64	41.48
BQTerrace	2.47	74.06	0.83	63.21	0.40	49.16	0.50	43.56

Average	0.83	75.91	0.62	68.30	0.35	54.49	0.37	42.22

Table 11. Performance comparisons with case 4

Sequence	Proposed (%)		PAPS (%) [4]		EETBS(%) [13]		FIICA (%) [14]	
	BDBR	TS	BDBR	TS	BDBR	TS	BDBR	TS
Traffic	-0.08	79.32	0.27	74.56	-0.40	53.47	-0.30	37.89
PeopleOnStreet	-0.15	79.37	0.29	61.23	-0.30	52.38	-0.23	40.15
Kimono	-0.33	79.44	0.28	71.25	0.33	70.83	0.21	60.18
ParkScene	-0.05	78.36	0.46	61.46	0.10	64.79	0.11	38.13
Cactus	0.89	77.00	0.55	71.12	0.50	43.17	0.72	39.29
BasketballDrive	1.68	74.11	2.01	65.69	1.50	46.73	1.70	42.74
BQTerrace	2.29	76.39	0.91	61.37	0.41	47.43	0.60	44.37
Average	0.61	77.71	0.68	66.67	0.31	54.11	0.40	43.25

In Table 8 (case 1), the average BDBRs of the proposed algorithm, PAPS, EETBS and FIICA are 0.02%, 0.30%, 0.20% and 0.06%, respectively. While the average TS of the proposed algorithm, PAPS, EETBS and FIICA are 79.45%, 67.03%, 55.34% and 47.15% correspondingly. In this case, the BDBR of the proposed algorithm is smaller than those of the other three algorithms, and the coding speed of the proposed algorithm is significantly faster than those of the other three algorithms. In Table 9 (case 2), the average BDBRs of the proposed algorithm, PAPS, EETBS and FIICA are -0.13%, 0.38%, -0.20% and -0.18%, respectively. While the average TS of the proposed algorithm, PAPS, EETBS and FIICA are 81.13%, 65.85%, 56.30% and 45.75% correspondingly. In this case, the BDBR of the proposed algorithm is smaller than that of PAPS and slightly larger than those of EETBS and FIICA. The coding speed of the proposed algorithm is significantly faster than those of the other three algorithms. In Table 10 (case 3), the average BDBRs of the proposed algorithm, PAPS, EETBS and FIICA are 0.83%, 0.62%, 0.35% and 0.38%, respectively. While the average TS of the proposed algorithm, PAPS, EETBS and FIICA are 75.91%, 68.30%, 54.49% and 42.22% correspondingly. In this case, the BDBR of the proposed algorithm is larger than those of the other three algorithms, meanwhile the coding speed of the proposed algorithm is significantly faster than those of the other three algorithms. In Table 11 (case 4), the average BDBRs of the proposed algorithm, PAPS, EETBS and FIICA are 0.61%, 0.68%, 0.31% and 0.40%, respectively. While the average TS of the proposed algorithm, PAPS, EETBS and FIICA are 77.71%, 66.67%, 54.11% and 43.25% correspondingly. In this case, the BDBR of the proposed algorithm is smaller than that of PAPS algorithm and negligibly larger than those of EETBS and FIICA algorithms, meanwhile the coding speed of the proposed algorithm is significantly faster than those of the other three algorithms.

In order to clearly demonstrate the performance of the proposed algorithm, Table 12 provides the overall average performance comparisons among these four algorithms with all four cases.

Table 12. Overall average performance comparison of the different methods

Case	Proposed (%)		PAPS (%) [4]		EETBS(%) [13]		FIICA (%) [14]	
	BDBR	TS	BDBR	TS	BDBR	TS	BDBR	TS
Case 1	0.02	79.45	0.30	67.03	0.21	55.34	0.06	47.15
Case 2	-0.13	81.13	0.38	65.85	-0.20	56.30	-0.18	45.75
Case 3	0.83	75.91	0.62	68.30	0.35	54.49	0.37	42.22
Case 4	0.61	77.71	0.68	66.67	0.31	54.11	0.40	43.25
Average	0.33	78.55	0.49	66.96	0.17	55.06	0.16	44.59

The overall average BDBRs of the proposed algorithm, PAPS, EETBS and FIICA are 0.33%, 0.49%, 0.17% and 0.16%, respectively. While the overall average TS of the proposed algorithm, PAPS, EETBS and FIICA are 78.55%, 66.96%, 55.06% and 44.59% correspondingly. Therefore, we can conclude that the coding speed of the proposed algorithm is significantly faster than those of the other three algorithms. Meanwhile, the BDBR of the proposed algorithm is smaller than that of PAPS algorithm and negligibly larger than those of EETBS and FIICA algorithms.

The main reasons why the proposed algorithm can effectively improve the coding speed are: (1) RCIM-BDES and RCD-BDET can be used to early skip and early terminate unlikely depths; (2) we can adopt RCIM-BMS to predict ILR mode so as to early skip unlikely Intra mode; (3) we use DD-BDS can skip many unnecessary DMs.

Generally speaking, the improvement of coding speed will lead to BDBR increase, namely coding efficiency decrease. However, from Table 8 to Table 12, we can sometimes observe coding efficiency increase, i.e., BDBR savings, on some sequences, when compared against the SHM reference software. One major reason is due to the Intra prediction process, in which CUs are predicted by their reference pixels. Apparently, if the texture of CUs and their reference pixels are more similar, their corresponding Intra prediction will be more accurate and RD costs will be smaller accordingly, and vice versa. For the current CU, different methods will lead to different neighboring CUs, which will lead to different reference pixels for the current CU, and in turn, lead to different RD costs for the current CU. In other words, compared to SHM, our method may therefore occasionally achieve either a decrease or an increase in BDBR [9].

V. CONCLUSION

In this paper, we have proposed a new Intra prediction algorithm for SSHVC. Since we observe some special features for SSHVC, and develop their corresponding strategies based on these features. The details are as follows: (1) most CUs use ILR mode and its prediction is very simple, we directly skip unlikely depths based on residual coefficients of ILR mode; (2) RD costs between ILR mode and Intra mode are significantly different, and both RD costs of ILR mode and Intra mode follow Gaussian distribution, we use GMM-EM to determine whether ILR mode is the best mode so as to skip Intra prediction; (3) when CUs use Intra mode, most CUs usually use DM 0, 1, 10, 26 and their neighboring DMs, we develop the corresponding strategy to search the best DMs, many unlikely DMs can be skipped. In our future research activities, we will use deep learning to improve the coding speed of SSHVC.

REFERENCES

1. X. G Liu, Y. Liu, P.C Wang, C.F Lai, and H.C Chao, "An Adaptive Mode Decision Algorithm Based on Video Texture Characteristics for HEVC Intra Prediction," IEEE Trans. Circuits Syst. Video Technol., vol. 27, no. 8, pp. 1737-1748, Aug. 2017.
2. X. G Liu, Y. Y Li, D. Y Liu, P.C Wang, and L. T. Yang, "An Adaptive CU Size Decision Algorithm for HEVC Intra Prediction based on Complexity Classification using Machine Learning," IEEE Trans. Circuits Syst. Video Technol., vol. 29, no. 1, pp. 144-155, Jan. 2019.
3. M. Xu, T.Y Li, Z.L Wang, X. Deng, R. Yang, and Z.Y Guan, "Reducing Complexity of HEVC: A Deep Learning Approach. IEEE Trans. Image Process," vol. 27, no. 10, pp. 5044-5059, Oct. 2018.
4. H. R. Tohidypour, M. T. Pourazad, and P. Nasiopoulos, “Probabilistic approach for predicting the size of coding units in the quad-tree structure of the quality and spatial scalable HEVC,” IEEE

Trans. Multimedia, vol. 18, no. 2, pp. 182–195, Feb. 2016.
5. H. R. Tohidypour, H. Bashashati, M. T. Pourazad, and P. Nasiopoulos, “Online-Learning-Based mode prediction method for quality scalable extension of the high efficiency video coding (HEVC) standard,” IEEE Trans. Circuits Syst. Video Technol., vol. 27, no. 10, pp. 2204–2215, Oct. 2017.
6. D. Wang, C. Zhu, Y. Sun, F. Dufaux, and Y. Huang, “Efficient multi-strategy intra prediction for quality scalable high efficiency video coding,” IEEE Trans. Image Process., vol. 28, no. 4, pp. 2063–2074, Apr. 2019.
7. D. Wang, Y. Sun, W. Li, C. Zhu, F. Dufaux, “Fast Inter Mode Predictions for SHVC,” in Proc. IEEE Int. Conf. Multimedia & Expo (ICME), Shanghai, China, Jul. 2019, pp.1696-1701
8. D. Wang, Y. Sun, W. Li, C. Zhu, F. Dufaux, "Fast Depth and Inter Mode Prediction for Quality Scalable High Efficiency Video Coding," IEEE Trans. Multimedia., vol. 22, no. 4, pp. 833-845, Apr. 2020.
9. D. Wang, Y. Sun, C. Zhu, W. Li, F. Dufaux, and J. Luo, "Fast Depth and Mode Decision in Intra Prediction for Quality SHVC," IEEE Trans. Image Process., vol. 29, no. 1, pp. 6136 - 6150, Dec. 2020.
10. L. Shen and G. Feng, “Content-based adaptive SHVC mode decision algorithm,” IEEE Trans. Multimedia, vol.21, no. 11, pp. 2714 -2725, Apr. 2019.
11. L. Shen, G. Feng and P. An, "SHVC CU Processing Aided by a Feedforward Neural Network", IEEE Trans. Industrial Informatics, vol. 15, no. 11, pp. 5803-5815, Apr. 2019.
12. X. Lu, C.Yu and G.R.Martin, "Efficient early termination and bypass scheme for CU size decision in spatially scalable SHVC intra coding," Electronics Letters, vol. 54, no. 22, pp. 1274-1276, Nov. 2018.
13. X. Lu, C. Yu, Y.F Gu, and G. Martin, "A fast Intra coding algorithm for spatial scalability in SHVC,” in Proc. IEEE Int. Conf. Image Processing (ICIP), Athens, Greece, Oct. 2018, pp. 1792-1796.
14. X. Lu, C.Yu and G.R.Martin, "Fast intra-and inter-coding algorithms for the spatially scalable extension of H.265/HEVC," Multimedia Tools and Applications(10.1007/s11042-020-09085-0)
15. H. R. Tohidypour, M. T. Pourazad, and P. Nasiopoulos, “Content adaptive complexity reduction scheme for quality/fidelity scalable HEVC,”in Proc. IEEE Int. Conf. Acoust., Speech Signal Process., Vancouver, BC, Canada, May 2013, pp. 1744-1748.
16. H. R. Tohidypour, H. Bashashati, M. T. Pourazad, and P. Nasiopoulos, “Fast mode assignment for quality scalable extension of the high efficiency video coding (HEVC) standard: A Bayesian approach,” in Proc. 6th Balkan Conf. Informat. BCI, Thessaloniki, Greece, 2013, pp. 61–65.
17. H. R. Tohidypour, M. T. Pourazad, and P. Nasiopoulos, “An encoder complexity reduction scheme for Quality/Fidelity scalable HEVC,” IEEE Trans. Broadcast., vol. 62, no. 3, pp. 664–674, Sep. 2016.
18. I.-M. Pao and M.-T. Sun, “Modeling DCT coefficients for fast video encoding,” IEEE Trans. Circuits Syst. Video Technol., vol. 9, no. 4, pp. 608–616, Jun. 1999.
19. N. Hu and E.-H. Yang, “Fast motion estimation based on confidence interval,” IEEE Trans. Circuits Syst. Video Technol., vol. 24, no. 8, pp. 1310–1322, Aug. 2014.
20. Z. Pan, S. Kwong, M. T. Sun, and J. Lei, “Early MERGE mode decision based on motion estimation and hierarchical depth correlation for HEVC,” IEEE Trans. Broadcast., vol. 60, no. 2, pp. 405–412, Jun. 2014.
21. W. Jiang, H. Ma, and Y. Chen, “Gradient based fast mode decision algorithm for intra prediction

in HEVC," in Proc.2nd Int. Conf. Consumer. Electron., Commun. Netw., Apr.2012, pp.1836-1840.
22. T. Zhang, M.T. Sun, D. B. Zhao, and W. Gao. Fast Intra-Mode and CU Size Decision for HEVC. IEEE Trans. Circuits Syst. Video Technol., vol. 27, no. 8, pp. 1714–1726, Aug. 2017.
23. M. Jamali, S. Coulombe, F. Caron, "Fast HEVC Intra Mode Decision Based on Edge Detection and SATD Costs Classification," Proceedings of Data Compression Conference, Snowbird, UT, USA, July 2015.
24. S. Q. Yan, L. Hong, W. F. He and Q.Wang, "Group-Based Fast Mode Decision Algorithm for Intra Prediction in HEVC," IEEE International Conference on Signal Image Technology and Internet Based Systems, Naples, Italy, November. 25-29, 2012.
25. H. Zhang, and Z. Ma, "Fast Intra Mode Decision for High-Efficiency Video Coding (HEVC)," IEEE Transactions on Circuits and Systems for Video Technology, vol.24, no.4, pp.660-668, Apr. 2014.
26. M. Jamali, and S. Coulombe. Fast HEVC Intra Mode Decision Based on RDO Cost Prediction. IEEE Transactions on Broadcasting, vol.65, no.1, pp.109-122, Mar. 2019.
27. Common SHM Test Conditions and Software Reference Configurations, document JCTVC-Q1009, ITU-T SG 16 WP 3 ISO/IEC JTC1/SC29/WG., Mar. 2014.
28. G. Bjontegaard, "Calculation of average PSNR difference between RD-curves," in Proc. 13th VCEG-M33 Meet., Austin, TX, USA, Apr. 2001, pp. 1–4.