A novel rate estimation model for mode decision of H.264/AVC

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ABSTRACT

To acquire the optimal coding mode of each macroblock, the H.264/AVC encoder exhaustively calculates the rate-distortion cost for all available modes and chooses the minimum one as the best mode. Therefore, the mode decision process is very computationally demanding. To reduce the computation complexity of the rate-distortion cost, in this paper, we propose a novel rate estimation model for the mode decision in H.264/AVC. By modeling the transform coefficients with Generalized Gaussian distributions (GGD), a direct relationship between the magnitude and the information bits of the quantized transform coefficients is deduced. Based on this deduction, the weighted sum of quantized transform coefficients is proposed as an efficient bit-rate estimator of the residual blocks. Extensive experiments show that the proposed algorithm can save up to 30% of total encoding time with ignorable degradation in coding performance for both inter- and intra-mode decision.

Keywords: Rate estimation, mode decision, rate-distortion optimization (RDO), Generalized Gaussian distributions (GGD), linear regression, H.264/AVC.

1. INTRODUCTION

To explore the coding efficiency of block-based hybrid video coding structure, coding strategies become more and more flexible during the development of international video coding standards such as MPEG-1, MPEG-2, MPEG-4, H.263 and the latest H.264/AVC. Lagrangian multiplier optimization technique is usually used to achieve the best coding mode decision in high-compression video coding. By using the optimization technique, all available modes are evaluated by rate-distortion (R-D) cost, and the one which minimizes the R-D cost is selected as the best mode. The minimization process of the R-D cost is well known as rate-distortion optimization (RDO). Although RDO can accurately choose the best mode for video coding, the computation complexity is very high.

To reduce the computational complexity of RDO in H.264/AVC, many fast mode-decision methods were proposed. Efforts were mainly dedicated to reduce the computation complexity in two ways. One is to explore the spatial characteristics of the pixels, with which the most probable Inter or Intra mode is predicted. Therefore unnecessary coding modes can be eliminated from the mode decision process. The other is to estimate the coding rate or distortion by a certain rate or distortion model. In this way, the coding rate of a certain mode is estimated to avoid actual entropy coding which costs much computation time. In the second category, rate models observed from quantizer (Q)-domain in [1] and ρ-domain in [2] are established and theoretically justified, but both models are only considered for rate control schemes. To reduce the complexity of RDO, block-level rate estimation models were also proposed. In [3], a linear function of the number and the levels of nonzero quantized transform coefficients is used as an efficient rate estimator, but this model is only designed for inter-mode decision. Another block-level rate estimation model using five different tokens of CAVLC is proposed in [4]. This model is suitable for both inter- and intra-mode decision of H.264/AVC, but it is constrained in the CAVLC entropy coding method.

In this paper, we propose a novel transform-domain rate estimation model. This model is derived from the direct relationship between bit rate and the magnitude of a single quantized transform coefficient. The model parameters are deduced from the GGD parameters of the transform coefficients and updated with linear regression during the encoding process.

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This paper is organized as follows: Section 2 discusses the relationship between bit rate and the magnitude of a single quantized transform coefficient. The proposed rate estimation model is introduced in Section 3. Section 4 presents the experimental results. Finally, conclusion is summarized in Section 5.

2. RELATIONSHIP BETWEEN BIT RATE AND QUANTIZED TRANSFORM COEFFICIENTS

The basic idea of the proposed rate estimation model originates from the observation that the same magnitude of different frequency components can result in different amount of information bits. For example, let F be the 4×4 quantized transform coefficients matrix in H.264/AVC, and a single frequency component is represented by $F(u,v)$. Then the information bits from "$F(3,3)=20$" is always more than the information bits from "$F(0,0)=20$". This is because $F(u,v)$ conforms to different distributions for different u or v, and the first event always happens with less probability than the second. The matrixes shown in Fig.1 are two actual quantized transform block of Foreman with CIF format. The l_I-norms of the 2 blocks are both 20. But the left block results in a coding rate of 62 bits, while the right block of which the power distributes to low frequency components results in a coding rate of only 28 bits. The matrixes shown in Fig.2 are also two actual quantized transform block of Paris with CIF format. The numbers of nonzero coefficients of the 2 blocks are both 10. But the left block results in a coding rate of 85 bits, while the right block of which the power is much lower results in a coding rate of only 27 bits. This demonstrates that even when the l_I-norms or the numbers of nonzero coefficients of two quantized transform block are exactly the same, the actual coding bits can be still very different. And the difference in the number of entropy coding bits is due to the different distributions of power in the transform block. Therefore, the magnitudes of quantized transform coefficients should be weighted before being used to estimate the bit rate.

$$F_0 = \begin{bmatrix} 2 & 1 & 2 & 1 \\ 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 \\ 3 & 1 & 2 & 0 \end{bmatrix}, F_1 = \begin{bmatrix} 16 & 2 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 1. Two actually coded quantized transform block from Foreman in CIF format with l_I-norm both equal to 20.

$$F_0 = \begin{bmatrix} 20 & 13 & 2 & 0 \\ 20 & 14 & 2 & 0 \\ 0 & 2 & 0 & 0 \\ 6 & 6 & 1 & 0 \end{bmatrix}, F_1 = \begin{bmatrix} 1 & 1 & 1 & 0 \\ 2 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{bmatrix}$$

Fig. 2. Two actually coded quantized transform block from Paris in CIF format with number of nonzero coefficient both equal to 10.

To get the exact weighting form, we start modeling the transform coefficients F_{uv} with a Generalized Gaussian distribution (GGD) [5] given by

$$f_{uv}(x) = \frac{\eta_{uv}\alpha(\eta_{uv})}{2\sigma_{uv}\Gamma(1/\eta_{uv})}\exp\left\{-[\alpha(\eta_{uv})\,|\frac{x}{\sigma_{uv}}|]^{\eta_{uv}}\right\}, \quad (1)$$

where $\Gamma(\cdot)$ is the gamma function, $\alpha(\eta_{uv}) = \sqrt{\Gamma(3/\eta_{uv})/\Gamma(1/\eta_{uv})}$, η and σ are positive real-valued distribution parameters which control the shape and scale of the GGD, respectively. We employ the GGD for analyzing the distribution of transform coefficients because it is a flexible distribution function which covers a wide range of symmetrical distributions. As shown in Fig. 3, for the special cases $\eta=1$, $\eta=2$ or $\eta=+\infty$, the GGD becomes a Laplacian, a Gaussian or a Uniform distribution. The GGD has already been widely and efficiently used for analyzing the distributions of transform coefficients in different research areas.

The quantization process suggested in H.264/AVC is represented by

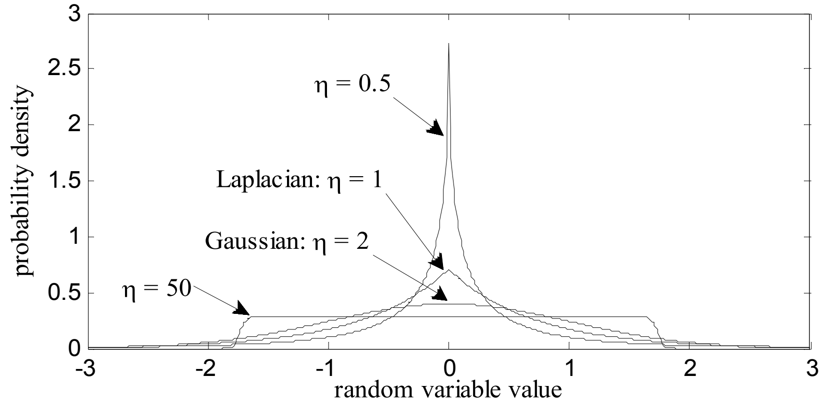

Fig. 3. Generalized Gaussian distribution with shape parameter η=0.5, 1, 2 and 50.

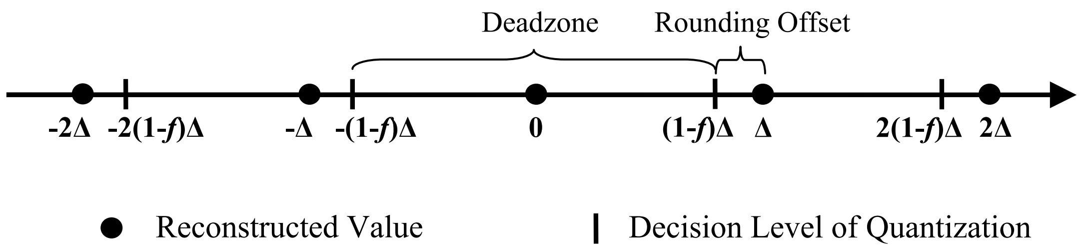

Fig. 4. The quantizer structure in H.264/AVC video coding.

$$|\hat{F}_{uv}| = (|F_{uv}|Q + f \cdot 2^{qbits}) >> qbits\,, \tag{2}$$

where Q is the multiplication factor and f is the rounding control parameter. An illustration of the quantizer structure is also shown in Fig.4.

With (2), the probability of F_{uv} being quantized as $\hat{x}$ is computed as

$$\mathrm{P}\left\{\hat{F}_{uv} = \hat{x}\right\} = \begin{cases} 2\int_0^{(1-f)\cdot Q_{step}} f_{uv}(x)dx, & \hat{x} = 0 \\ \int_{(|\hat{x}|-f)\cdot Q_{step}}^{(|\hat{x}|+1-f)\cdot Q_{step}} f_{uv}(x)dx, & \hat{x} \neq 0 \end{cases}, \tag{3}$$

where Q_{step} is the quantizer step size equaling to $2^{qbits}/Q$. The information bits from "$\hat{F}_{uv} = \hat{x}$" is

$$r_{uv} = -\log_2 \mathrm{P}\left\{\hat{F}_{uv} = \hat{x}\right\}. \tag{4}$$

Observe that the GGD is a continuous monotonic decreasing function when $x \geq 0$, it can be obtained that there exists a x^* in the quantization interval which satisfies

$$\mathrm{P}\left\{\hat{F}_{uv} = \hat{x}\right\} \approx \begin{cases} 2(1-f)Q_{step}f_{uv}(x^*) & \hat{x} = 0 \\ Q_{step}f_{uv}(x^*) & \hat{x} \neq 0 \end{cases}. \tag{5}$$

Due to the convexity of the GGD function with shape parameter lying between 0 and 1, the value of x^* can be promised to be in the first half of the quantization interval, i.e., $x^* \in [(\hat{x}-f)\cdot Q_{step}, (\hat{x}-f)\cdot Q_{step} + 0.5\cdot Q_{step}]$. According to [6], the rounding control parameter f in (2) is set below 1/2 to better locate the expectation value of $\widehat{F}_{uv}$ inside a quantization interval. Therefore, we approximate the value of x^* with $\widehat{x}$ when $\widehat{x} \neq 0$, and the probability of "$\widehat{F}_{uv} = \widehat{x}$" can be approximated by

$$\mathrm{P}\left\{\hat{F}_{uv} = \widehat{x}\right\} \approx \begin{cases} 2(1-f)Q_{step} \cdot f_{uv}(f \cdot Q_{step}) & \widehat{x} = 0 \\ Q_{step} \cdot f_{uv}(\widehat{x} \cdot Q_{step}) & \widehat{x} \neq 0 \end{cases}. \tag{6}$$

With (5) and (6), when $\widehat{x} \neq 0$, the information bits from "$\widehat{F}_{uv} = \widehat{x}$" is approximated by

$$r_{uv} \approx -\log_2\left\{Q_{step} \cdot \frac{\eta_{uv}\alpha(\eta_{uv})}{2\sigma_{uv}\Gamma(1/\eta_{uv})} \exp\left\{-[\alpha(\eta_{uv})\,|\frac{Q_{step} \cdot \widehat{x}}{\sigma_{uv}}|]^{\eta_{uv}}\right\}\right\} = \mathrm{a}_{uv} \cdot \left|\widehat{x}\right|^{\eta_{uv}} + \mathrm{b}_{uv}, \tag{7}$$

where

$$\begin{cases} \mathrm{a}_{\mathrm{uv}} = \log_2(e) \cdot [Q_{step} \cdot \alpha(\eta_{uv}) / \sigma_{uv}]^{\eta_{uv}} \\ \mathrm{b}_{\mathrm{uv}} = \log_2[Q_{step} \cdot \eta_{uv}\alpha(\eta_{uv}) / (2\sigma_{uv}\Gamma(1/\eta_{uv})] \end{cases}. \tag{8}$$

The derivation of r_{uv} when $\widehat{x} = 0$ is similar to (7), but a_{uv} and b_{uv} have different values. Then for transform coefficients having Generalized Gaussian distributions, the amount of information bits is a power function of their magnitudes. Observe that when η_{uv}=1, the GGD becomes a Laplacian distribution, and (7) becomes a simple linear function. Because $1/\sigma_{uv}$ is always larger with a larger index of u and v, and $a_{uv}=\log_2(e)\cdot[Q_{step}\cdot 2^{1/2}/\sigma_{uv}]$, it can be observed that the high frequency coefficients with larger u and v can affect the bit rate more than the low frequency coefficients. This result verifies the effect that different frequency components of quantized transform coefficients can affect the bit rate differently.

3. PROPOSED RATE ESTIMATION METHOD

According to the information theory, the number of information bits from a composite signal is equal to the sum of information bits of its independent components. And the independence of the transform coefficients is satisfied to a great extent according to [7] and [8]. For the good decorrelation ability of the discrete cosine transform, with (7), the amount of information bits of a quantized transform block can be approximately computed by

$$r_B \approx \sum_u \sum_v (\mathrm{a}_{uv} \cdot \left|\hat{x}_{uv}\right|^{\eta} + \mathrm{b}_{uv}). \tag{9}$$

Due to the strong correlation between the entropy coding bits and the information bits, we propose to estimate the actual coding bits of a single block with the information bits in (9) as

$$R_B = \alpha \cdot r_B + \beta, \tag{10}$$

where α and β are the parameters of the proposed rate estimation model, R_B is the estimated coding bits of a single block.

3.1 Implementation of the proposed rate estimation algorithm

Based on (7), (9) and (10), the proposed rate estimation algorithm is implemented by the following four steps:

1. Assign the GGD parameters of the current frame with the GGD parameters of previous frame of the same type. This means that we assign the GGD parameters of current I frame with the GGD parameters of the previous I frame, and the parameter assignment for P or B frame is similar.
2. Calculate the a_{uv} and b_{uv} in (9) by (8) for each of the 16 coefficients in a 4×4 block with the GGD parameters obtained in step 1.
3. During the mode decision process of encoding the current frame, we implement the following steps for each block as:

a) Compute the information bits of current quantized transform block coefficients by (9) with the estimated GGD parameters obtained in step 1.

b) Compute the estimated bit rate of current quantized transform block coefficients by (10) with the block information bits computed in step 3-a).

c) Use the estimated bit rate for mode decision, and select the best coding mode *k*.

d) After entropy coding of the current block with the selected mode *k*, we record the actual entropy coding bits *R* and update the mode parameters using *R*. The updating process has been illustrated in detail in section 3.3.

4. Estimate the GGD parameters of the current frame type with the statistics of the quantized transform coefficients obtained in the current frame. The implementation of estimating the GGD parameter has been introduced in detail in section 3.2.

The quantized transform coefficients used in the above four steps were recorded in the transform module. And the entropy coding is replaced by the proposed rate estimation algorithm during mode decision process. To accelerate our algorithm, we pre-calculated the information bits in (7) at the start of encoding current frame for possible quantized values. And the results are saved in a lookup table to avoid redundant calculation of the power function in (9). Therefore, the calculation of information bits in step 3-a) is actually implemented with a simple table look-up operation.

3.2 Estimation of GGD parameters

Several methods have been proposed for estimating the distribution parameters of the GGD, and these methods are based on the mathematical relationship between the moments and the parameters given by

$$R(\eta) = \frac{\Gamma^2(2/\eta)}{\Gamma(1/\eta)\Gamma(3/\eta)} = \frac{E^2\{|X|\}}{E\{X^2\}}, \tag{11a}$$

$$\sigma^2 = E\{X^2\}, \tag{11b}$$

where $E\{X\}$ and $E\{X^2\}$ represent the one-order moment and two-order moment of the random variable X, respectively. With Equations (11a) and (11b), the GGD parameters η and σ can be estimated by

$$\hat{\eta} = R^{-1}\left(\frac{\left(\frac{1}{N}\sum_{i=1}^{N}|X_i|\right)^2}{\frac{1}{N}\sum_{i=1}^{N}X_i^2}\right), \quad \hat{\sigma} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}X_i^2}\ . \tag{12}$$

A simple hyperbola function $H(x)$=0.2718/(0.7697-x)-0.1247 is used in [9] to directly approximate the inverse function of $R(x)$ in (11a) for fast parameter estimation of GGD. In this paper, we employ this method to estimate the GGD parameters for its simplicity and efficiency.

For the actual encoding process, statistics of the transform coefficients in current frame can only be available when the entire frame has been encoded. To solve this problem, we propose to estimate the GGD parameters of current frame by the GGD parameters of previous frame of the same type.

3.3 Updating of model parameters

To make the model adaptive to variously changing frame statistics, we update the model parameters α and β with linear regression. The linear regression process is expressed by

$$R_i = \alpha \cdot r_i + \beta + \varepsilon_i, \tag{13}$$

where i=0,1,…,n-1, R_i represents the actual coding bits by the entropy coder, r_i represents the information bits computed by (9), ε_i is the prediction residual error. The least square estimates of model parameters α and β are given by

$$\alpha = \frac{n\sum_{i=0}^{n-1} R_i r_i - \sum_{i=0}^{n-1} R_i \sum_{i=0}^{n-1} r_i}{n(\sum_{i=0}^{n-1} r_i)^2 - \sum_{i=0}^{n-1} r_i^2}, \beta = \frac{n(\sum_{i=0}^{n-1} r_i)^2 \sum_{i=0}^{n-1} R_i - \sum_{i=0}^{n-1} R_i r_i \sum_{i=0}^{n-1} r_i}{n(\sum_{i=0}^{n-1} r_i)^2 - \sum_{i=0}^{n-1} r_i^2}. \quad (14)$$

Observe that during the linear regression process, as the number of blocks utilized for updating the model parameters α and β increases, the sensitivity to the new data gradually decreases. To fix this problem, we reset the linear regression process by initializing the n, R_i and r_i in (14) with zero when n has reached a given threshold value T_{update}. We also observe that at the start of the linear regression process, the updated model parameters α and β can be unstable due to the lack of available data. To handle this situation, we propose to start the updating process only when n has reached a given threshold value $T_{threshold}$.

4. EXPERIMENTAL RESULTS

Note that the overall encoding complexity reduction of all fast mode decision algorithms is greatly relied on the version of the reference software. And the ratio of encoding complexity reduction could be lower if the algorithms are performed on a later version of the reference software. We integrated the proposed algorithm into a recent version of H.264/AVC reference software JM13.2. Experiments are performed at different QP values ranging from 24 to 39, and some important coding parameters are set as: all available inter- and intra-modes in reference software are enabled; fast motion estimation algorithm "Simplified UMHexagon" is used; motion search range is 33 by 33; the number of reference frames is 1 for IPP coding type and 2 for IBP coding type; IntraPeriod is set as 8; CABAC entropy coding method is used; Fast chroma intra mode decision is turned off.

Table. 1. Coding performance of the proposed algorithm (Compared to RDO in H.264/AVC for QCIF sequences).

Sequence	Type	ΔPSNR(dB)[5]	ΔTotal(%)	Sequence	Type	ΔPSNR(dB)[5]	ΔTotal(%)
Foreman	IPP..	-0.0484	11.6%	Container	IPP..	-0.0718	11.9%
	IBP..	-0.0233	11.4%		IBP..	-0.0533	9.1%
Bus	IPP..	-0.0363	14.6%	Hall_monitor	IPP..	-0.0558	9.7%
	IBP..	-0.0362	13.7%		IBP..	-0.0523	9.4%
Football	IPP..	-0.0529	14.0%	Mother_daughter	IPP..	-0.0674	7.9%
	IBP..	-0.0534	12.2%		IBP..	-0.0368	5.7%
Tempete	IPP..	-0.0327	18.3%	Silent	IPP..	-0.0599	11.5%
	IBP..	-0.0386	16.2%		IBP..	-0.0500	9.4%
Coastguard	IPP..	-0.0292	13.5%	Stefan(352x240)	IPP..	-0.0419	16.6%
	IBP..	-0.0336	10.5%		IBP..	-0.0646	13.8%

Table. 2. Coding performance of the proposed algorithm (Compared to RDO in H.264/AVC for CIF sequences).

Sequence	Type	ΔPSNR(dB)[5]	ΔTotal(%)	Sequence	Type	ΔPSNR(dB)[5]	ΔTotal(%)
Coastguard	IPP..	-0.0296	14.1%	Paris	IPP..	-0.0461	15.6%
	IBP..	-0.0292	10.6%		IBP..	-0.0403	13.1%
Bus	IPP..	-0.0411	15.3%	Tempete	IPP..	-0.0303	16.8%
	IBP..	-0.0443	12.6%		IBP..	-0.0360	12.6%
Forman	IPP..	-0.0381	9.9%	Flower	IPP..	-0.0410	18.2%
	IBP..	-0.0366	7.5%		IBP..	-0.0394	14.3%
Football	IPP..	-0.0634	11.8%	Container	IPP..	-0.0558	11.1%
	IBP..	-0.0635	10.8%		IBP..	-0.0446	8.6%
Mobile	IPP..	-0.0357	20.6%	Silent	IPP..	-0.0466	18.4%
	IBP..	-0.0343	16.3%		IBP..	-0.0402	19.1%

To verify the robustness of our proposed rate estimation algorithm, extensive experiments were performed on standard test sequences with QCIF and CIF format. In the experiment, we mainly compare the complexity reduction and the coding performance loss [10] of the proposed algorithm. When evaluating the complexity reduction, we use ΔT in [4] defined as $\Delta T = [(T_{RDO} - T_{Proposed})/T_{RDO}] \times 100\%$, where T_{RDO} and $T_{Proposed}$ represent the average computation time of the encoder with the original RDO and with the proposed algorithm, respectively. The experimental results listed in Table 1 and Table 2 show that the average PSNR loss [10] compared with original RDO is ignorable, while the proposed algorithm can achieve 5% to 30% of total encoding time reduction depending on QP value ranging from 24 to 39, and on average about 13% of total encoding time reduction. To verify the accuracy of the proposed algorithm, the actual and the estimated bit rate of randomly selected 160 blocks in Foreman with CIF format is shown in Fig. 5. From Fig. 5 it can be seen that our proposed algorithm can estimate the rate efficiently. The R-D performance of the proposed algorithm compared with RDO turned on and without RDO is also shown in Fig.6.

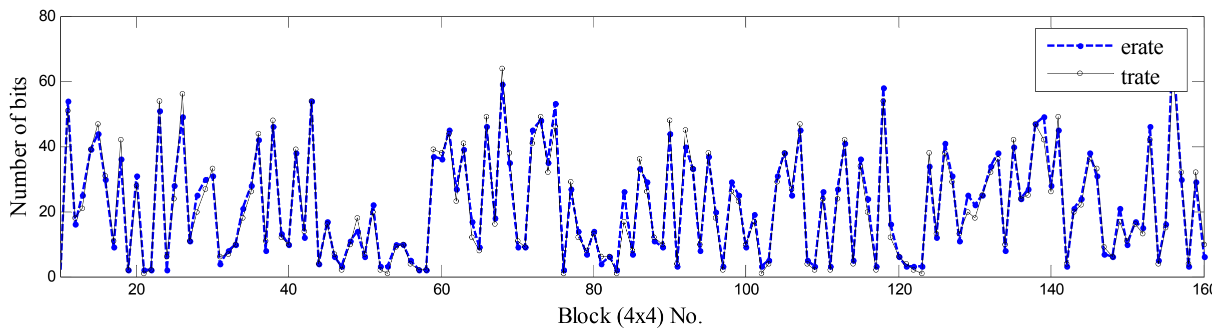

Fig. 5. Comparisons of the actual and the estimated block rate of consecutive 100 blocks in Foreman with CIF format.

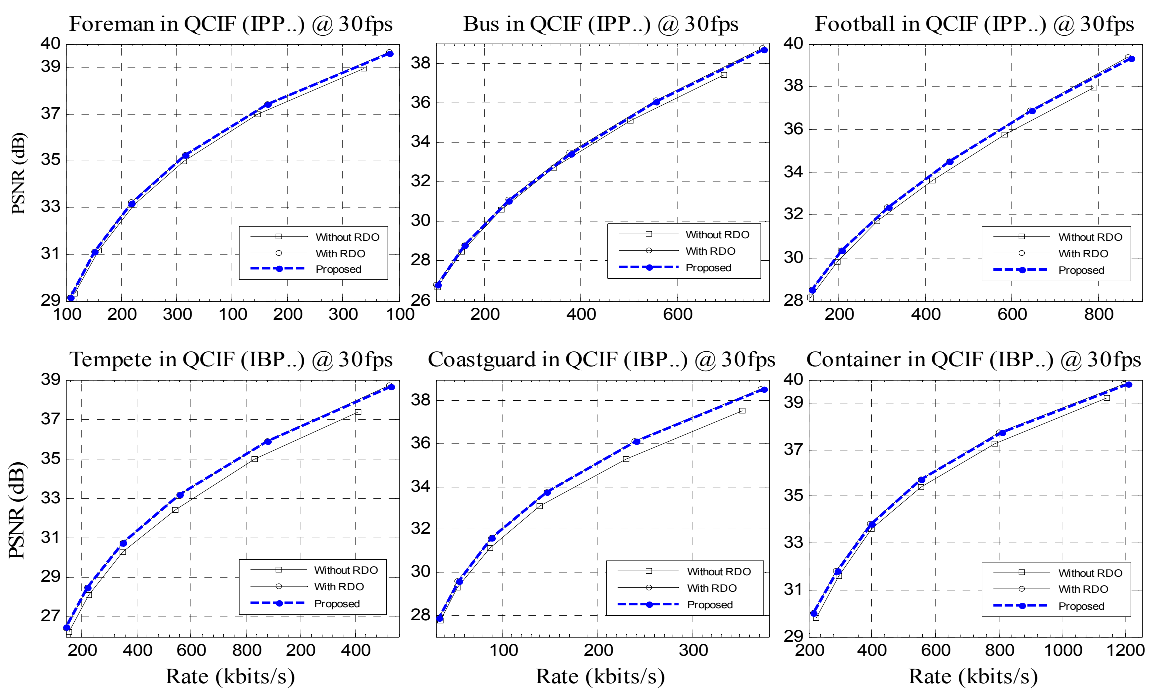

Fig. 6. Performance comparisons of different mode decision algorithms in H.264/AVC reference software JM13.2.

In Fig. 7, we compare the efficiency of our proposed model with the other existing rate estimation models [3] using the number of nonzero coefficients and the l_1-norm of the quantized transform block. From Fig. 7, we can see that the estimated bits using information bits calculated by (9) in our proposed model are more compactly and linearly distributed. Compared with the rate estimation model in [3], our proposed rate estimation model is efficient in coding performance for both inter- and intra-mode decision in H.264/AVC. Different from the rate model in [4], the proposed model is not constrained in the properties of CAVLC entropy coding. Although only experimental results with CABAC entropy coding are shown here, experiments show that the proposed mode is also efficient for CAVLC entropy coding.

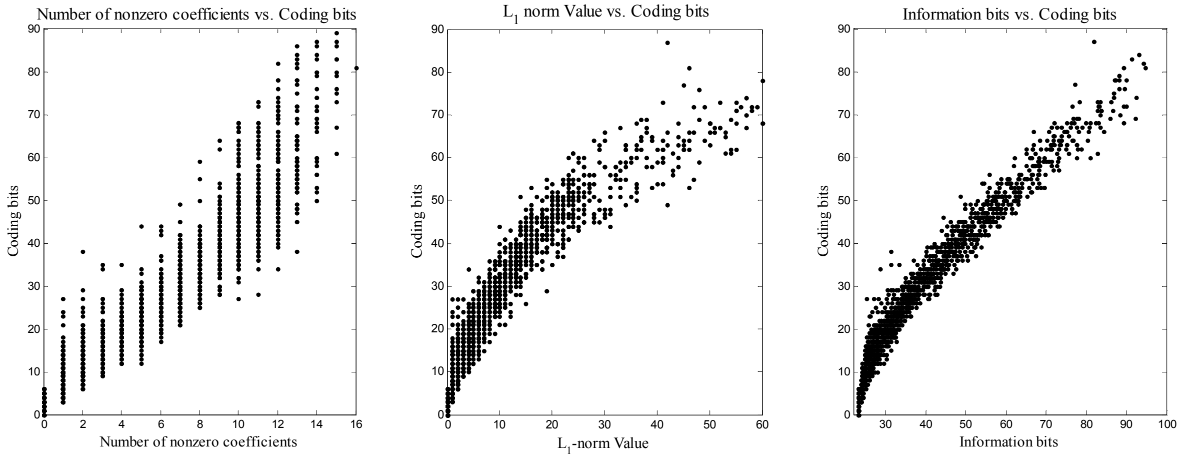

Fig. 7. Comparisons of different bit-rate estimators in Foreman with CIF format

5. CONCLUSION

In this paper, we propose an adaptive transform-domain bit-rate estimation model for the mode decision in H.264/AVC. The rate estimation model uses the weighted sum of quantized transform coefficients as an efficient rate estimator. Extensive experimental results show that, for both intra- and inter-mode decision, the proposed algorithm can estimate the rate efficiently without actually performing entropy coding. Ignorable degradation of coding performance compared with original RDO is achieved and up to 30% of total encoding time can be saved.

6. ACKNOWLEDGEMENT

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