Wavelet-Based Image Compression System with Linear Distortion Control

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Abstract: - In this paper, an optimized quantization of wavelet transform coefficients and low complex distortion control system for image compression is proposed. Distortion control is an important issue in maintaining the desired quality in the retrieved signal of compressed data. We construct a linear relationship between the distortion and quantization scale, which is crucial for efficient quality maintenance due to its simplicity and accuracy. This method can provide wavelet-based image data compression with a precise linear prediction model, resulting in high compression performance. A genetic algorithm (GA) is used to optimize the indices of distortion and compression ratio (CR). The optimization can induce linear relationships among multi-level quantization scales and enable the control of multi-level quantization scales with a single variable. Then a curve fitting technique is used to produce the quantization scales formula which is controlled by a single value. The experimental results showed that the proposed method can obtain better compression performance and distortion control exactly as predicted, with low complexity.

Key-Words: - distortion control, genetic algorithm, image coding

1 Introduction

Images acting as instruments of information transmission are the most popular media tool on the internet. Since images inherently contain significant amounts of data, image compression is crucial for efficient transmission and storage. One image compression technique which cannot offer perfect reconstruction of the original data is called lossy compression otherwise called lossless compression [1]. Lossy compression entails the permanent loss of some original image information to yield a high CR result. The compromise between high CR and distortion usually greatly depends on transmission control and user satisfaction. The information loss occurs during the quantization process [2]. Therefore, a quantization scheme will strongly impact compression performance due to irreversible processing. Optimization schemes generally can be partitioned into filter selection and quantization scale design groups. With lattice parameterization, Nielsen et al. [3] proposed a signal-based optimization process that found the optimal mother wavelet with minimal distortion rates for some fixed CRs. He and Mitra [4] designed an optimal quantization error feedback filter by minimizing synthesis filtering errors. Filter selection is also a concern in 3D signal compression [5]. These methods optimize the compromise between compression ratio (CR) and distortion, but do not consider the capability of quality control before coding. GA offers a robust method for both searching and optimization [6], with wide applications in numerical optimization. In our method, GA is used to optimize the indices of distortion and compression ratio

At the present time, the estimation of image and video quality also plays an important role in image and video broadcasting, i.e., transmission control, because the quality is a criterion determinant of user satisfaction and a key indicator of transmission quality. Therefore, quality prediction of an image is important and many works have focused on this topic. For optimizing the compromise, reconstruction quality of compressed image should be precisely predictable. A quality prediction survey can be achieved from the quality measurement of received images [7-11]. The automatic quality measurement methods can assign quality scores to images or videos in meaningful agreement with subjective human assessment of quality. Such methods can be used to monitor image and video quality for a quality control system and can be employed to benchmark image and video processing systems. These researches can be divided into three categories: full-reference metrics, reduced-reference metrics and no-reference metrics [11]. For limitless bandwidth communication, maintaining reconstruction quality is an essential requirement for lossy image compression [17, 20]. These works predict the image quality before encoding the image data (JPEG2000). [17] indicated that it is necessary for rate allocation [12, 13], filter selection [14] and encoding parameter decisions [15, 16]. [14] experimentally created a relation between spatial and frequency indices of filter banks with the quality for a bit-rate. Many methods establish models of quality prediction; [15, 16] grouped videos into various categories and built quality vs. bit-rate curve for every category. [17] produced a model which integrates image feature and CR together; the image quality at various CRs can be predicted without coding. The PSNR difference is less than 2db for over 95% of the images. [20] proposed a pre-compression quality-control(PCQC) algorithm to solve the complex embedded block coding (EBC) with optimized truncation (EBCOT) tier-1 of JPEG2000. The rate and distortion of coding passes is approximately predicted by using the propagation property and the randomness property of the EBC algorithm. The drawback of the method is that the average peak-signal-to-noise ratio (PSNR) degrades about 0.1~0.3 db and the PSNR difference is smaller than 1.5db at the range of 25 to 45 db. EBCOT tier-2 is used to find a set of optimal truncation points for all the code-blocks. The set of optimal truncation points gives an overall bitstream length that is within the desired rate. Therefore, the individual code-block streams have the property that they can be truncated to a variety of lengths $R^1, R^2, \ldots, R^n$ and distortion $D^1, D^2, \ldots, D^n$. EBCOT calculates the rate-distortion slope values of all passes for each code-block by the following equation: $S_i^{z_i} = \frac{\Delta D_i^{z_i}}{\Delta R_i^{z_i}}$ [20], where and mean the difference of Mean Squared Error (MSE) and the difference of number of code bytes between the z-th and (z-1)th truncation point for the ith code-block, respectively. If there are some values of slope that do not follow the rule that becomes smaller, we should delete this kind of truncation points to avoid $S_i^{z_i} > S_i^{z_i - 1}$. EBCOT can iterate a few cycles to find the optimum truncation points for the best quality of the compressed image at the desired bit rate. A simple algorithm to find the optimal truncation point, z_i^{λ}, which minimizes $(D_i^{z_i^{\lambda}} + \lambda R_i^{z_i^{\lambda}})$, is as follows:

Initialize ; $z_i^{\lambda} = 0$

for =1,2,3,…

set $\Delta R_i^x = R_i^x - R_i^{z_i^{\lambda}}$ and $\Delta D_i^x = D_i^x - D_i^{z_i^{\lambda}}$;

if $\frac{\Delta D_i^x}{\Delta R_i^x} > \lambda$ then update $z_i^{\lambda} = j$.

In addition to rate control, EBCOT can also minimize the total rate R at the target distortion; this is called quality control. As the rate control, optimal quality control is achieved by minimizing $\sum\left(R_i^{z_i} + \lambda' D_i^{z_i}\right)$, where λ' is the Lagrange multiplier for quality control, as is the Lagrange multiplier for rate control.

Currently, image and video are widely used, and quality prediction is important for transmission control, user satisfaction, etc. In this paper, the 9/7 wavelet, which is the most popular wavelet filter, is used in our transform coding. The 9/7 filter is the default filter of the JPEG2000 standard and the MPEG4 standard because of its good performance. We propose that the wavelet coefficients can be quantized by non-uniform quantization scales in different subbands. Use a variable value to calculate the quantization scales and to predict the image quality at the pre-coding stage without inverse quantization, wavelet transform coding and decoding of Set Partitioning in Hierarchical Trees (SPIHT) [19]. Based on the linear programming, a linear quantization scale prediction model can automatically guarantee the desired quality for reconstructed signals with a few iterations. The result of our experiment shows that our method has higher PSNR than SPIHT does at the same CR, and the predicted PSNR of quality control is close to the target PSNR.

The remainder of this paper is organized as follows. In section 2, GA is briefly described. In addition, we express how to produce the different quantization scales in GA and how to design the parameters of GA. We discuss our proposed method in section 3. The experiment results are illustrated in section 4 and a conclusion is offered in section 5.

2 Problem Formulation

2.1 The Wavelet-Based Image Compression System with Linear Distortion Characteristic

The proposed method encoding processes involves three functional blocks: the 9/7 wavelet transform, quantization and lossless SPIHT coding, as shown in Fig. 1. The decoding process also works with inverse direction. Original image signals will be transformed into wavelet coefficients d_j^* by the 9/7 wavelet filter; d_j^* is a vector consisting of the wavelet coefficients of the *j*th level. The subband coefficients will be quantized for dynamic range reduction that derives the quantized data $\bar{d}*$ with:

$$\bar{d}* = \left\lfloor \frac{d_0^*}{c_0(QF)}, \frac{d_1^*}{c_1(QF)}, \cdots, \frac{d_j^*}{c_j(QF)} \right\rfloor$$

where $\lfloor X \rfloor$ denotes the truncation of the elements of vector into an integer, and $c_j(QF)$ is the quantization scale of the *j*th level. In the inverse quantization process, each retrieved datum will be compensated by half of the quantization scale, namely:

$$\hat{d}* = \left(\bar{d}* + 0.5sign\left(\bar{d}*\right)\right) \times c_j(QF)$$

where denotes the sign vector of , e.g., given , then $sign\left(\bar{d}*\right) = [-1,1]$.

$c_j(QF)$ is an adjustable parameter controlled by the single variable *QF*. The multi-level quantization scheme using single control variable is favorable for data compression. Then, the *QF* and quantized data will be encoded with the lossless SPIHT scheme due to the high efficiency.

Guaranteeing the quality of reconstructed data is an important feature required for image compression. One simple approach for this requirement is using an error control loop that recursively adjusts the quantization scale until the reconstruction error is located in a specified small region. To this end, GA optimization followed by a curve fitting is applied for the value determination of $c_j(QF)$. The former improves the compression performance and the latter transforms the distortion curve into a linear control. GA optimization is based on a competition of using 60 images which are divided into six different datasets according to the entropy. We calculate the entropy of all of the images; then the entropy of two of the six datasets is low, high for another two of them, while the others are medium. The $c_j(QF)$ determination process consists of three steps described as follows:

Step 1: By using six datasets, find the seven quantization schemes by two processes, i.e., GA optimization and curve fitting.
Step 2: Apply each quantization scheme for all databases where the signals with compression performance will be recorded.
Step 3: Choose the one with best compression performance as the desired quantization scheme.
The specification of GA optimization is defined in the following:
Objective: Find the values of $c_j(QF)$, $-18 \leq j \leq 0$.
Fitness function:Minimizing the ratio of (1/PSNR)/CR
Group size:100 sets with each set defined as:

$$\{(c_0(\,), c_1(\,), c_2(\,)), \cdots, c_{18}(\,)\}.$$

Selection:Eighty sets with smallest (1/PSNR)/CR are selected for crossover in each iteration.
Crossover:
1)The choice of $\{c_0(\,), \cdots c_{18}(\,)\}$ for crossover is random where the value of j is also randomly chosen.
2) Crossover processing number for each iteration is defined as 40.

Mutation:
1)Mutation process is defined as exchanging the values of $c_i(\,)$ and $c_j(\,)$ when they are selected.
2)The mutation probability is defined as 0.3.
Termination:
1)Iteration times should exceed 150.
2)Select the set with minimum (1/PSNR)/CR and terminate the iteration.

For evolution, the mutation strategy can effectively increase convergence speed. There are six $\{c_0(\,), \cdots c_{18}(\,)\}$ sets generated in every dataset; we calculate the performance of six sets by using the seven $\{c_0(\,), \cdots c_{18}(\,)\}$ sets and select the best $\{c_0(\,), \cdots c_{18}(\,)\}$. For the desire of linearly controlling $c_j(\,)$ generation, we introduce another set which is *QF*=15, with the average 1/PSNR1=0.046387 of 60 images and we assume that *QF*=0 means there is no quantization values; then 1/PSNR=0 because of PSNR=∞ . Only considering the behavior of PSNR, we introduce 19 quadratic equations for fitting the 19 curves of $c_j(\,)$ using a single control variable *QF*. The $c_j(QF)$ corresponds to $PSNR_n$ with $QF = (1/\mathrm{PSNR}_n)/(1/\mathrm{PSNR}_1)$. The coefficients of

19 quadratic equations are found by curve fitting. $c_j(QF)$ are given in the follow

C_1 = 0.2689×QF^3-6.2364×QF^2+50.4051×QF - 133.9474

C_2 = 0.2664×QF^3-6.1768×QF^2+49.9104×QF - 132.5439

C_3 = 0.2547×QF^3-5.8338×QF^2+46.7632×QF - 123.5992

C_4 = 0.2695×QF^3-6.2752×QF^2+50.8589×QF - 135.3308

C_5 = 0.2714×QF^3-6.324×4QF^2+51.3357×QF - 136.8375

C_6 = 0.2695×QF^3-6.2685×QF^2+50.8232×QF - 135.3724

C_7 = 0.2751×QF^3-6.433×QF^2+52.3333×QF - 139.7041

C_8 = 0.2714×QF^3-6.3209×QF^2+51.2746×QF - 136.6183

C_9 = 0.2728×QF^3-6.3627×QF^2+51.6754×QF - 137.7979

C_{10} = 0.2724×QF^3-6.3505×QF^2+51.5742×QF - 137.5351

C_{11} = 0.2721×QF^3-6.3402×QF^2+51.4686×QF - 137.2094

C_{12} = 0.2722×QF^3-6.3431×QF^2+51.4876×QF - 137.2441

C_{13} = 0.2705×QF^3-6.2953×QF^2+51.0688×QF - 136.084

C_{14} = 0.2717×QF^3-6.33×QF^2+51.3816×QF - 136.9783

C_{15} = 0.272×QF^3-6.3394×QF^2+51.473×QF - 137.2517

C_{16} = 0.2719×QF^3-6.3364×QF^2+51.4443×QF - 137.1664

C_{17} = 0.2718×QF^3-6.3326×QF^2+51.4098×QF - 137.0696

C_{18} = 0.2716×QF^3-6.3275×QF^2+51.3665×QF - 136.9526

C_{19} = 0.2719×QF^3-6.3392×QF^2+51.4837×QF - 137.3087

2.2 The Linear Dynamic Error Control Scheme

In this section, highly efficient quality predetermination and control schemes are proposed. The reconstructed error is predicted by the wavelet coefficients in the frequency-domain. In other words, it is without the inverse quantization process and inverse wavelet transform in the quality control loop for low computational complexity. For our compression system, the errors are produced by e_Q, which is the truncation process after quantization, and the e_B round-off process of reconstructing data. The quantization process will produce an error e_Q such that $\frac{d^*}{c(QF)} = \tilde{d}^* + e_Q$, where the e_Q is less than one, $|e_Q| < 1$. Let $Sign(e_Q)$ denotes the sign of e_Q, where the e_Q is positive or negative. Thus $Sign(e_Q) = Sign(\hat{d}^*) = Sign(d^*)$. e_B denotes the round-off error of the reconstruct data with $|e_B| < 0.5$. We define $qe' = c(QF)(e_Q - 0.5Sign(e_Q))$ where qe' means the differences between $\hat{d}^*$ and $\bar{d}^*$. For reducing the complexity of PSNR computation, it only uses the e_Q value in transform domain. To this end, we propose a simplified PSNR (SPSNR) parameter for the distortion measurement such as:

$$\text{SPSNR} = 10\log_{10}\frac{(255)^2}{\text{SMSE}}$$

where SMSE is the simplified mean square error between $\hat{d}^*$ and $\bar{d}^*$. We define the SMSE as:

$$\text{SMSE} = \frac{(qe')^2}{M \times N}$$

where M and N are the height and width of the image. The computation of SPSNR does not need the process of inverse quantization and inverse wavelet transform. Using SPSNR can reduce more of the complexity of distortion measurement than PSNR can. Fig. 2 shows the relationships between SPSNR and PSNR; our curve is the average result of 18 images selected from the six databases. SPSNR is ever closer to the PSNR when the PSNR is ever high. Even in low PSNR, the difference between SPSNR and PSNR is less than 0.4 dB, as shown in Fig. 3.

For the goal of error control, we proposed a high efficient error prediction and control system. In this system, a dynamic linear *QF* determination algorithm is proposed and the error of wavelet coefficients is calculated in the frequency domain for obtaining low complexity. This algorithm can predetermine the *QF* factor according to the desired PSNR with less iteration. The entire compression procedure and the *QF* prediction algorithm are given in the following steps.

Step 1: Initial setting: target quality (PSNRt); a *QF* (QF_r); control loop (n); error bound (ε)

Step 2: Wavelet coefficients will be quantized by a *QF*(n)

Step 3: Using $QF_1 = ((1/\text{PSNR}_t) - 0.0044)/0.002634$ for the SPSNR1 predetermination

Step 4: if ($\left|\mathrm{PSNR}_t - \mathrm{SPSNR}_r\right|$) >ε, then:

4.1) n+1

4.2) if n=1, then:

$$QF_2 = QF_1 \times \left(\frac{\frac{1}{\mathrm{PSNR}_t} - 0.0044}{\frac{1}{\mathrm{SPSNR}_r} - 0.0044} \right)$$

Then QF2 will get a SPSNR2

4.3) if loop>1, then:

$$QF(n) = \frac{(((QF_1 - QF_2) \times (((1/\mathrm{PSNR}_t) - (1/\mathrm{SPSNR}_2))))}{(((1/\mathrm{SPSNR}_1) - (1/\mathrm{SPSNR}_2)))} + QF_2$$

4.4) $QF_2 \rightarrow QF_1$

SPSNR2→ SPSNR1

$QF(n) \rightarrow QF_2$

$\mathrm{SPSNR}_n \rightarrow \mathrm{SPSNR}_2$

go to Step 4 until $\left|\mathrm{SPSNR}_n - \mathrm{PSNR}_t\right|$ <ε

Step 5: Lossless SPIHT coding

3 Problem Solution

In this section, the performance of the proposed method was studied in some experiments. In the comparison with schemes SPIHT and [18], the performance evaluation was based on 4 images (Lena, GoldHill, Baboon and Pepper) which are gray level 512×512 pixels. The compressed data file consists of a *QF* value and quantized data. The former was encoded with the lossless SPIHT scheme. Tables 1 and 2 show the compression performance results, where the value denotes the PSNR of a CR. The proposed method can obtain better performance, especially for the low CR region. In the best case, the quality can improve about 0.2~0.46 db, and the quality degrades less than 0.03db in the worst case. The results show that the proposed quantization scheme can obtain much better compression performance.

In the study of distortion control, the Lena, Baboon, Jet and Pepper were tested for the comparison with [19]. Distortion control precision signifies how close it is between the target PSNR and the result PSNR. Tolerable bound ε was considered in the closed-loop error control process. Tables 3 and 4 show the result of our proposed method when ε<0.1 dB and Tables 5 and 6 show another result when ε<0.5 dB. [19] is not suitable for the distortion control at low CR because of the degrading reconstruction quality of about 0.5dB~1dB, and the difference of true PSNR is less than 1.5 dB at the range 25 to 45. The experimental results show that the quality of our method is usually better than SPIHT and the distortion control precision is always smaller than ε. According to the target PSNR, we calculate the *QF*(n) with a few iterations. Due to the near linear relationship between *QF* and PSNR, we can predict the PSNR precisely with low complexity. The evaluation results with good compression performance and quality control capability show that the proposed quantization scheme is well applicable for image signals.

4 Conclusion

For efficient distortion control and compression performance of wavelet-based image data, a single quantization value method has been proposed for the design of a linear distortion quantization scheme in this paper. The GA showed that the criterion of minimal (1/PSNR)/CR can induce a linear relationship among multi-level quantization scales. This implies that multi-level quantization scales can be generated with a single variable, which can easily control the reconstruction error and save the bits of all levels' quantization scales for the adaptive quantization scheme. As shown by the experimental results, the compression performance is similar to SPIHT at high CR, and is better than SPIHT at low CR. Compared with [19] for distortion control, the precision is less than ε which is set by users. The distortion control of our proposed method can be suitable for any rates.

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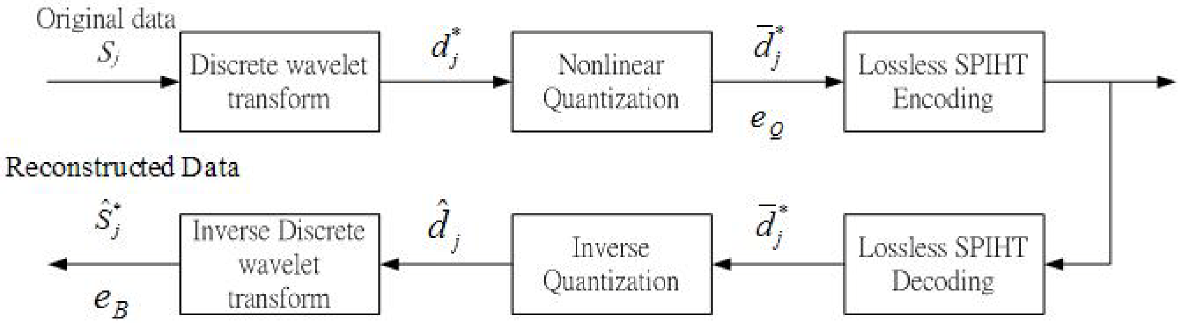

Figure 1: Function block of our image compression system

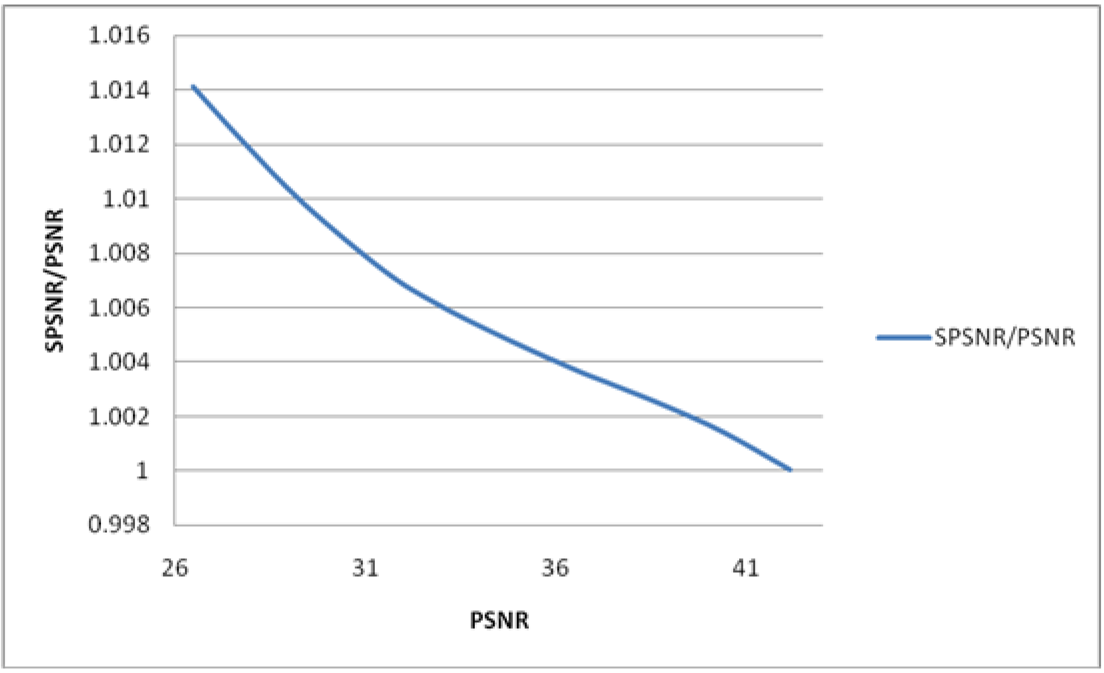

Figure 2: The relationship between SPSNR and PSNR

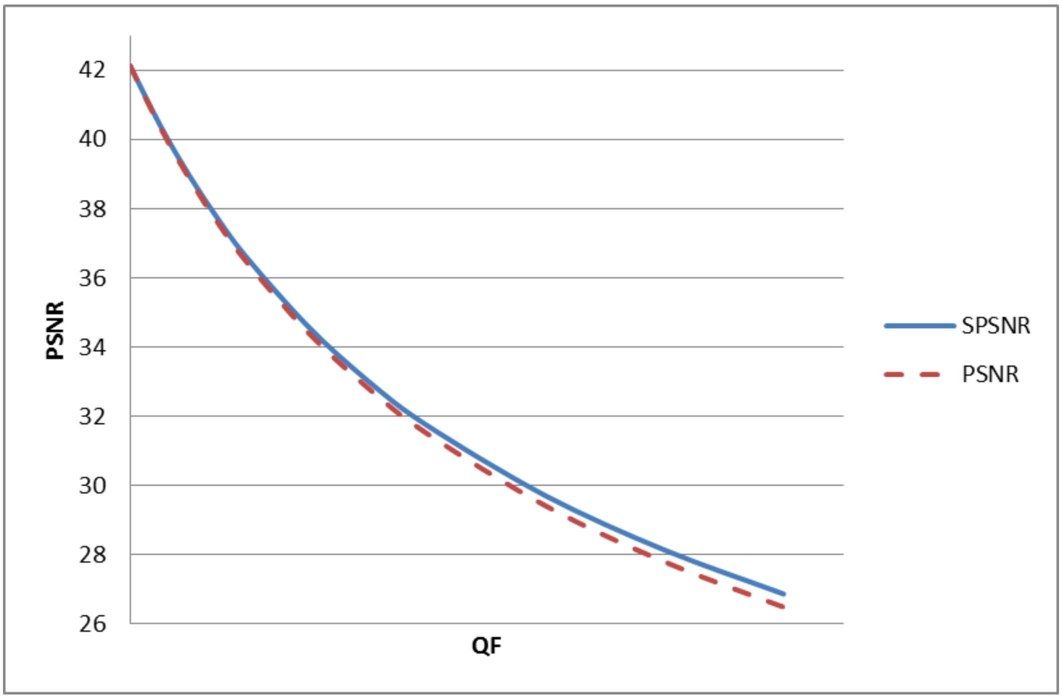

Figure 3: The difference between SPSNR and PSNR

Table 1: Coding performance comparison with SPIHT

Lena	GoldHill

CR	PSNR(db)			CR	PSNR(db)		
	Our method	SPIHT	Difference		Our method	SPIHT	Difference
4.647212	45.07429	44.7396	0.334688	3.678633	44.57476	44.23289	0.341875
8.606137	40.42824	40.33517	0.093067	6.533693	39.63116	39.52091	0.11025
13.90795	37.80353	37.69083	0.1127	10.5312	36.69698	36.50683	0.190152
30.90455	33.93583	33.92171	0.014115	26.35871	32.44118	32.37333	0.067853
86.13595	29.52814	29.53139	-0.00325	86.00878	28.59523	28.6487	-0.05347
209.8411	26.29834	26.33695	-0.03861	263.1968	25.81583	25.81955	-0.00372

Table 2: Coding performance comparison with SPIHT

Baboon				Pepper			
CR	PSNR(db)			CR	PSNR(db)		
	Our method	SPIHT	Difference		Our method	SPIHT	Difference
2.266023	45.0045	44.54318	0.461319	2.912942	44.46559	44.01915	0.446439
3.323974	38.98984	38.80431	0.185527	5.131187	38.6967	38.50353	0.193167
4.681341	35.13858	34.97298	0.165599	9.057485	35.64015	35.57732	0.062827
9.693644	29.57177	29.52392	0.047847	24.33851	32.30901	32.31517	-0.00616
29.95418	24.32885	24.32273	0.006118	58.31902	28.88807	28.90834	-0.02027
143.1699	21.22655	21.2375	-0.01095	132.8741	25.21469	25.23355	-0.01886

Table 3: Quality control performance of proposed method when ε<0.1db

Lena				Baboon			
Target PSNR	QF	Result SPSNR	iteration	Target PSNR	QF	Result SPSNR	iteration
45	6.304889	44.9722	4	45	6.341662	44.94827	4
40	7.433406	40.04962	3	40	7.178976	39.99259	4
37	9.43489	36.93708	3	37	8.341653	36.99074	3
34	11.026	34.00845	4	34	9.55046	34.02023	2
30	13.11233	29.95852	3	30	10.98456	29.93475	1
27	14.95527	27.04595	3	27	12.05315	27.00476	3
24	17.41647	24.08057	3	24	13.3188	23.99278	3

Jet				Pepper			
Target PSNR	QF	Result SPSNR	iteration	Target SPSNR	QF	Result PSNR	iteration
45	6.344959	44.92711	3	45	6.278116	45.00496	5
40	7.820805	39.90976	1	40	7.041315	39.95394	4
37	9.521409	37.01233	4	37	8.268273	37.00083	3
34	10.85156	34.01534	4	34	9.995467	33.99596	3
30	12.56249	30.07202	2	30	12.54501	30.00224	4
27	14.07533	27.04835	3	27	14.38552	26.99643	4
24	15.92162	23.96251	3	24	16.20815	24.01354	3

Table 4: Quality control performance of proposed method when ε<0.1db

Table 5: Quality control performance of proposed method when ε<0.5db

Lena				Baboon			
Target PSNR	QF	Result SPSNR	iteration	Target PSNR	QF	Result SPSNR	iteration
45	6.322163	45.31637	2	45	6.382994	44.53914	3
40	7.820805	39.92916	1	40	7.138607	40.13385	3
37	9.708059	36.87946	3	37	8.430909	36.79093	2
34	11.26063	33.7572	3	34	9.495735	34.16649	1
30	13.15257	29.98144	3	30	10.98456	29.93475	1
27	14.75006	27.35777	2	27	11.94095	27.30121	2
24	17.04121	24.45195	2	24	13.20528	24.21164	2

Table 6: Quality control performance of proposed method when ε<0.5db

Jet				Pepper			
Target PSNR	QF	Result SPSNR	iteration	Target PSNR	QF	Result SPSNR	iteration
45	6.309362	45.22191	2	45	6.291113	44.85643	4
40	7.820805	39.90976	1	40	6.936028	40.37694	3
37	9.599702	36.85507	3	37	8.432672	36.70667	2
34	10.92156	33.83392	3	34	9.773956	34.36877	2
30	12.56249	30.07201	2	30	12.63127	29.8634	3
27	14.20493	26.76823	2	27	14.11358	27.47935	2
24	16.08429	23.76531	2	24	16.44172	23.66521	2