JND-based Multiple Description Image Coding

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Abstract

In this paper, a novel multiple description image coding (MDC) scheme is proposed, which is based on the characteristics of the human visual model. Due to the inherent characteristics of human vision, the human eye can only perceive the change of the specific thresholds, that is, the just noticeable difference (JND) thresholds. Therefore, JND model is applied to improve MDC syetem. This paper calculates the DCT coefficients firstly, and then they are compared with the JND thresholds. The data that is less than the JND thresholds can be neglected, which will improve the coding efficiency. Compared with other existing methods, the experimental results of the proposed method are superior.

Keywords: multiple description image coding, just noticeable difference (JND), DCT coefficients

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1. Introduction

In high speed network environment, multimedia information is very important [1] [2]. However, the traditional packet-based data transmission usually faces the problem of packet loss or error, which will affects the efficiency of information transmission. In recent years, multiple description coding (MDC), as an effective solution, has begun to be concerned. When only one description is received, the information can be recovered roughly but acceptable. And the quality of the reconstruction will be better with the increase of the received descriptions [3]-[5].

In the past years, a variety of MDC methods has been proposed. In [6], Vaishampayan designs the source quantizer skillfully, and puts forward a new multiple description scalar quantization (MDSQ) scheme, which is asymptotically near optimal at high rates [7]. In [8], a two-stage modified MDSQ (MMDSQ) is also close to the optimal.

The MDSQ method is extended to more than two descriptions in [9]. Then, in [10], MDLVQ is presented Source splitting is another method of MDC. In [11], source separation is designed firstly, where, the source is divided into odd and even samples, and each subset is encoded with DPCM.

Transform coding is used in JPEG 2000 with two rates for two descriptions in [12], which is called RD-MDC. Then RD-MDC is extended to more than two descriptions in [13], where each JPEG 2000 is also coded with two rates. In [14], a multiple rates method is presented. In this method, M different rates are applied to code each subset.

In [15], the pairwise correlating transform (PCT) ,which govern the redundancy by a set of 2 $\times$2 correlating transform, is presented. If one coefficient is lost, its counterpart in the other description can estimate it. However, PCT has poor performance at high rates, because linear prediction [16] [17] is used to predict redundancy, which is similar to the method in [11]. In [18], a generalized PCT (GPCT) encoding the prediction residual of each description is proposed.

In [19], a prediction compensated MDC (PCMDC) method is proposed in the light of two-descriptions coding. The source is divided into two subsets, each of them is coded, and the coding result is used as the basis for one description. Each description also encodes the predictive redundancy of another subset. In the image coding based on overlapped transform, the application of MDLTPC is better than MMDSQ, RD-MDC, PCT, and GPCT.

In [20], two methods of MDC are proposed. One is multiple description coding with randomly offset quantizers (MDROQ), the other is multiple description coding with uniformly offset quantizers (MDUOQ), where the closed-form expression of theoretical performances is obtained for any value of M.

In the MDC schemes mentioned above, the characteristics of the human visual system (HVS) are not fullly considered. The human eye is the final receiver of the image, so it is necessary to optimize encoding algorithm using human visual characteristics. Using human visual characteristics to optimize the image coding algorithm can make the coding more in line with human subjective experience. So this paper adopts a DCT-based JND model in the MDC framework, and it can accurately match with HVS. JND refers to the various visual masking effects of HVS, which means that the human eye can only perceive the signal changes beyond the JND thresholds.

In this paper, the JND model is applied to the MDC schemes to remove more visual redundancy and improve the coding efficiency. JND model is a kind of model based on psychology and physiology, which can effectively represent the human visual redundancy in the image. At present, several JND models have been proposed, which can be divided into two categories: JND model based on pixel domain in [21] and JND model based on transform domain in [22]. And they are applied at the encoder and decoder, respectively. At the encoder, the DCT coefficients of an original image are obtained firstly, and then the DCT coefficients are compared with the DCT-based JND thresholds. At the decoder, the pixel domain JND thresholds, obtained by the DCT-based JND ones, are then used to process the errors between the original image and the compressed image.

The remainder of this paper is arranged as follows. In Section 2, we describe the scheme proposed in this paper and its advantages. In Section 3, the proposed method is compared with others, and results are given.

2. JND-BASED MULTIPLE DESCRIPTION IMAGE CODING

In this section, we first introduce the framework of the proposed JND-based MDC scheme, then specific steps of the two JND-based MDC methods are described. At last, theoretical analysis and expression of the expected distortion are given.

2.1 Overview

In the proposed MDC method, to get M descriptions, the sources are divided into M subsets. We can partition the sources at block level or sample level. For example, we can divide the sources into two subsets at block level, as shown in **Fig. 1**. Each descripton includes two subsets. In description 0, S0 is encoded with small stepsize q_0, S1 is predicted from the already encoded subset S0, and the prediction residuals of S1 are quantized by a large stepsize q_1. Correspondingly, in description 1, S1 is encoded with small stepsize q_0, while S0 is predicted from the already encoded subset S1, and the prediction residuals are quantized by a large stepsize q_1.

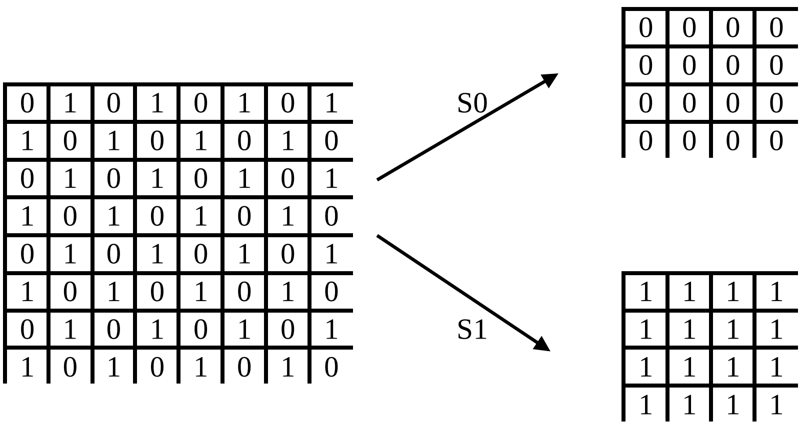

Fig. 1. Two subsets resulted from the sources

Time-domain lapped transform (TDLT) proposed in [23] is applied to the proposed MDC scheme. At the TDLT scheme, a M×M prefilter P and T are applied to the two block boundaries, where M represents the block size. Besides, M-point DCT and IDCT are applied to each block. Matrix P and T have the following structures to generate a near optimal linear phase overlap transformation [23]:

$$P = Wdiag\{I,V\}W \tag{1}$$

$$T = P^{-1} = Wdiag\{I,V^{-1}\}W \tag{2}$$

$$W = \frac{1}{\sqrt{2}}\begin{bmatrix} I & J \\ J & -I \end{bmatrix} \tag{3}$$

where I is an $M/2 \times M/2$ identity matrix, V is an $M/2 \times M/2$ invertible matrix, and J is an $M/2 \times M/2$ counter-identity matrix.

In the proposed MDC scheme, DCT-based JND model is applied. The JND value based on DCT is usually expressed as a base threshold multiplied by a number of factors [24]. And, the corresponding JND model expression is:

$$JND(r,c,i,j) = JND_{Basic}(r,c,i,j) \times JND_{lum}(r,c,i,j) \times JND_{contrast}(r,c,i,j) \tag{4}$$

where r and c are represented as the index of a block in an image, i and j as the index of the DCT coefficients ($i,j=1:8$). Besides, $JND_{Basic}(r,c,i,j)$, $JND_{lum}(r,c,i,j)$ and $JND_{contrast}(r,c,i,j)$ represent spatial contrast sensitivity function(CSF), brightness adaptive weighting factor, and contrast masking weighting factor respectively.

$JND_{Basic}(r,c,i,j)$ is a spatial contrast sensitivity function(CSF), which represents the sensitivity of HVS to the visual signal, and it is affected by the spatial frequency of the visual signal.

$$JND_{Basic}(r,c,i,j) = \frac{s}{\phi_i \phi_j} \cdot \frac{\exp(c\omega_{ij})/(a+b)\omega_{ij}}{r+(1+r)\bullet\cos^2(\varphi_{i,j})} \tag{5}$$

where s represents a collection effect, and its empirical value is 0.25, ϕ_i and ϕ_j are the normalization factor of DCT, ω_{ij} is the corresponding spatial frequency of the DCT sub-band coefficients at the (i,j) position, $r+(1+r)\cdot\cos^2(\varphi_{i,j})$ represents the tilt efficiency of the human eye $(r=0.6)$, and $\varphi_{i,j}$ represents the direction angle of the corresponding DCT component. Besides, the three parameters a , b and c are set to 1.33, 0.1 and 0.18.

$JND_{lum}(r,c,i,j)$ is the brightness adaptive weighting factor. The luminance masking factor is used to measure the weight of the perceived error in a stable background, which only depends on the characteristics of the local image. The brightness adaptive weighting factor is expressed as follows.

$$JND_{lum}(r,c,i,j) = \begin{cases} (60-\bar{I})/150+1 & \bar{I} \le 60 \\ 1 & 60 < \bar{I} < 170 \\ (\bar{I}-170)/425+1 & \bar{I} \ge 170 \end{cases} \tag{6}$$

where $\bar{I}$ represents the average brightness.

$JND_{contrast}(r,c,i,j)$ is a contrast masking weighting factor that is usually associated with the perceived degree of a signal in the presence of another signal. In the calculation, the image is first Canny edge detection, image blocks are divided into three categories: smooth area, edge area and texture area, different regions have different weights. The weighted factor of smooth region and the edge region is $\psi=1$, and the texture region if the coefficient index satisfies the condition $(i^2+j^2)\le 16$, then $\psi=2.25$, otherwise $\psi=1.25$. Considering the masking effect between the adjacent sub-bands, the contrast masking weighting factor is obtained:

$$JND_{contrast}(r,c,i,j)=\begin{cases}\psi, & for\ \ (i^2+j^2)\le 16\ \ in\ \ Plan\ \ and\ \ Edge\ \ Block\\ \psi\cdot\min(4,\max(1,(\dfrac{C(r,c,i,j)}{JND_{Basic}(r,c,i,j)}\times JND_{lum}(r,c))^{0.36})) & others\end{cases}\tag{7}$$

2.2 System Description

In this paper, we mainly study the JND-based two description image coding. **Fig. 2** is the block diagram of JND-based MDLTPC (Multiple Description Lapped Transform with Prediction Compensation) [14], while **Fig. 3** is the block diagram of JND-based MDROQ. In this paper, $x(k)$, $s(k)$ and $y(k)$ on behalf of the input of prefilter, the input of DCT and the output of DCT, respectively, and $\hat{x}(k)$ denote reconstrction of the *k*th block.

2.2.1 System Description of JND-based MDLTPC

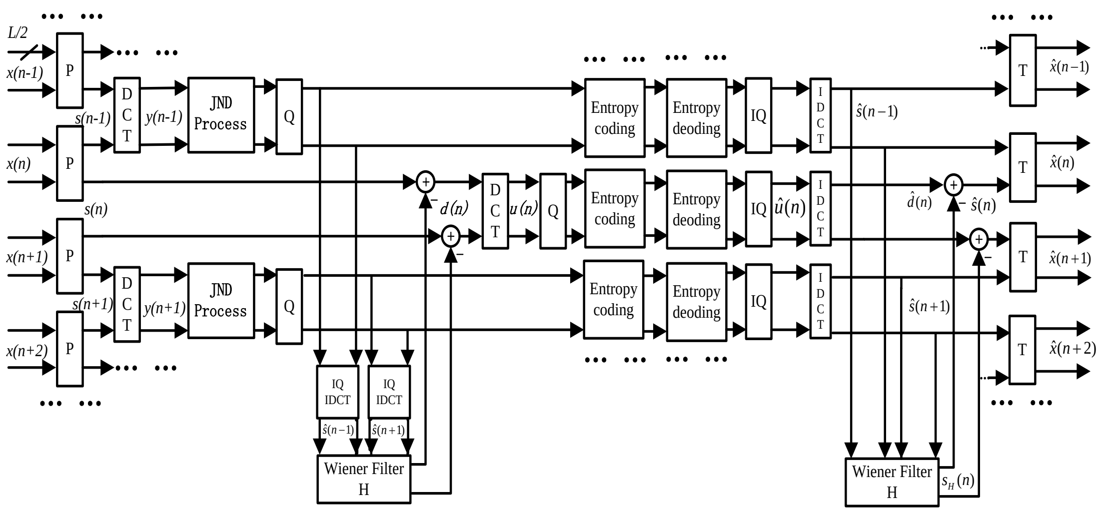

Fig. 2. The block diagram of JND-based MDLTPC

Fig. 2 illustrates the encoding and decoding process of one description of the proposed JND-based MDLTPC. Another description can be obtained in the same way.

At the encoder, for the base layer, after the prefilter P and M-point DCT transform, the JND model is introduced to make the DCT coefficients be sparse, firstly. The DCT coefficients are compared with the DCT-based JND thresholds (4). The data that is less than the JND thresholds can be neglected, while others are retained, this will improve the coding efficiency under the premise of ensuring the visual quality. Then, quantization and entropy coding are applied successively. For the enhancement layer, the prefiltered blocks $\{s(k)\}$ plus minus the estimated data from the encoded base layer blocks firstly. Then, the prediction residuals are DCT transform, quantization and entropy coding.

At the decoder, if two descriptions are received, only the base layer blocks of the two descriptions are used, where entropy decoding, the inverse quantization, the inverse DCT and the postfilter T are applied successively. If only one description is received, entropy decoding, the inverse quantization and the inverse DCT are applied to the base and enhancement layer blocks of the received description successively, firstly. Then enhancement blocks are estimated from the received base layer blocks by Wiener filter before postfiltering. At last, the postfilter T is used for reconstrction.

2.2.2 System Description of JND-based MDROQ

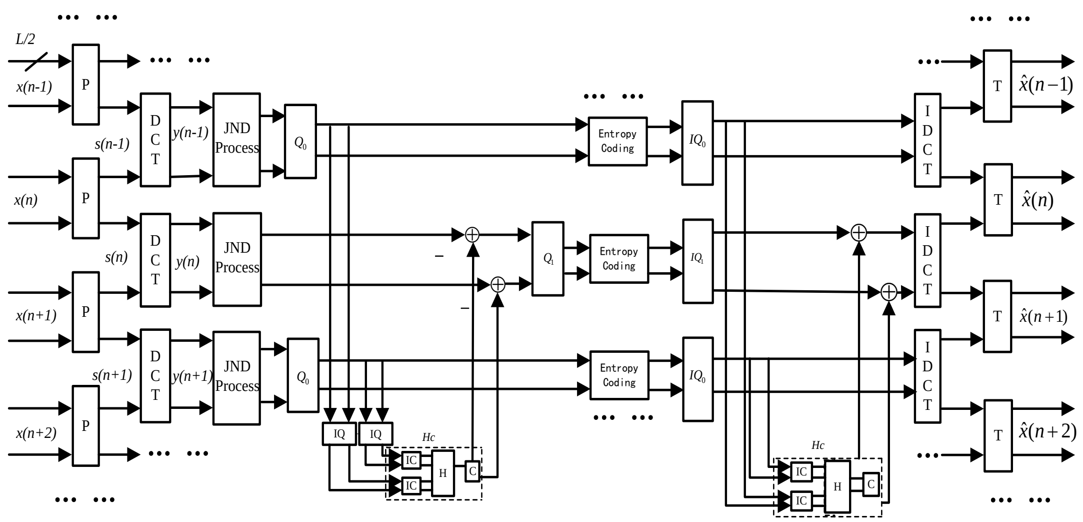

Fig. 3. The block diagram of JND-based MDROQ.

Fig. 3 illustrates the encoding and decoding process of one description of the proposed JND-based MDROQ. Another description can be obtained in the same way.

At the encoder, the JND model is used to make the DCT coefficients be sparse after the prefilter P and M-point DCT transform. The DCT coefficients are compared with the DCT-based JND thresholds. The data that is less than the JND thresholds can be neglected while others are retained, which will improve the coding efficiency under the premise of ensuring the visual quality. For the base layer blocks, quantization and entropy coding are applied successively after DCT transform. For the enhancement layer blocks, $\{y(n)\}$ the out of DCT transform blocks plus minus the estimated data from the encoded base layer blocks firstly. Then the prediction residuals are quantization and entropy coding.

At the decoder, if only one description is received, entropy decoding and the inverse quantization are applied to the base and enhancement layer blocks of the received description successively, firstly. Then enhancement blocks are estimated from the received base layer blocks before the inverse DCT. At last, the inverse DCT and the postfilter T are used for reconstrction. If two descriptions are received, we first get the reconstructed values of each description using the method of receiving a description. Then, finding out the intersection of all received quantization bins is the key to reconstruct each subset.

Fig. 4 is a two-description coding example of reconstructing each subset. x is the original data of subset S0, $\hat{x}_i$ is the reconstruction of x in description 0, $\bar{x}_1$ is the prediction of x in description 1, $\hat{e}_1$ is the reconstrction of the prediction residual e_1. When both descriptions are received, a refined reconstrcution $\hat{x}_{q_0,q_1}$ of x can be got. We can reconstruct subset S1 in the same way.

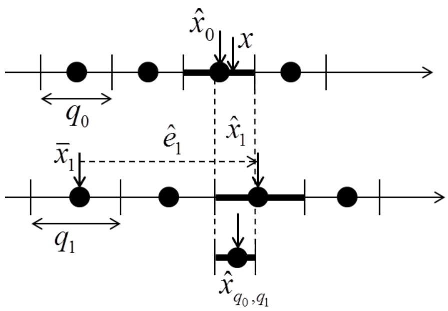

Fig. 4. a two-description coding example reconstructing each subset

2.3 Theoretical Analysis and Expected Distortion Expression

According to the theory of compressive sensing, the sparsity of the signal is of decisive significance to the reconstruction of the signal. With the increase of signal sparsity, the decoding complexity of the signal will be reduced, and the reconstruction effect will be improved [25] [26]. In this paper, the block DCT transform is used as a sparse basis.

Table 1. The number of zero DCT cofficients

Test images	The number of zero DCT coefficients			
	Berfore JND processing		After JND processing	
	MDLTPC	MDROQ	JND_MDLTPC	JND_MDROQ
Lena	0	0	100816	201370
Boat	0	0	98765	197460
Peppers	0	0	97702	195442
Couple	0	0	90509	180910
Goldhill	0	0	88936	177625
Baboon	0	0	68631	137110

No matter **Fig. 2** or **Fig. 3**, the JND model is introduced to further make the DCT coefficients be sparse. The JND model is used to filter the DCT coefficients of the six test images, and the DCT coefficients below the JND threshold are set to zero. As shown in **Table 1**, it can be seen that a lot of DCT coefficients become zero after the JND processing, the signal becomes sparser. This also shows that the sparsity of the DCT coefficients is increased without affecting the subjective quality.

In the proposed MDC scheme, each description consists of half of the base layer samples and half of the enhancement layer samples. Assuming that R_0 and R_1 respectively represent the average bit rate of the base layer and the enhancement layer, then the total rate R [bits/pixel (bpp)] is $R = R_0 + R_1$. If the total bit rate R and the missing probability p are fixed, we can adjust R_0 and R_1 to minimize the expected distortion, that is, maximum the Expected PSPNR.

Let D_0 and D_1 denote central distortion and side distortion when two descriptions and one description are received, respectively. Then the expected distortion can be writen as:

$$D = (1-p)^2 D_0 + 2p(1-p)D_1 \tag{8}$$

3. EXPERIMENTAL RESULTS FOR JND-BASED MD IMAGE CODING

3.1 Evaluation Criterion

In this section, we evaluate the performance of the proposed scheme in this paper. In order to compare with other methods fairly, this paper sets up the same experimental parameters for MDC. It should be noted that the peak signal-to- perceptual ration (PSPNR) in [21] is used as the criterion for evaluating the quality of image reconstruction. The PSPNR in this paper can be calculated as:

$$PSPNR = 10\log_{10} \cdot \frac{255 \times 255}{\frac{1}{WH}\sum_{x=1}^{W}\sum_{y=1}^{H} |I(x,y) - \hat{I}(x,y)|^2 \, \delta(x,y)} \tag{9}$$

and

$$\delta(x,y) = \begin{cases} 1, \ if \ |I(x,y) - \hat{I}(x,y)| \geq Pixel\_JND(r,c,x,y) \\ 0, \ otherwise \end{cases} \tag{10}$$

where $I(x,y)$ and $\hat{I}(x,y)$ respectively represent the original value and the reconstructed value of the pixel located at (x,y). W and H denote the width and height of the image. $Pixel\_JND(r,c,x,y)$ represents JND values of pixel domain.

Both the pixel domain JND and the frequency domain JND are derived from the same human vision mechanism, so they can be transformed into each other [27] [28]. **Fig. 5** is a block diagram from JND values of DCT domain to JND values of pixel domain.

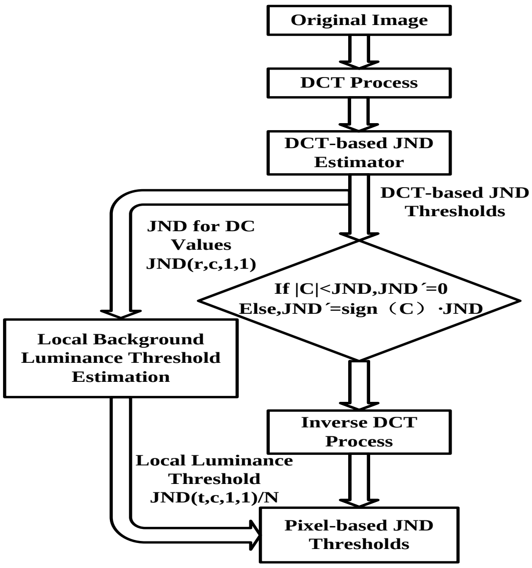

Fig. 5. JND values of DCT domain to JND values of pixel domain.

3.2 Results

The performance comparisons of the proposed JND-based MDC method with MDLTPC and MDROQ are implemented in one description-loss environment and two descriptions receive environment. Six 512×512 standard test images with different characteristics are selected in this paper, and the block size M is chosen to be 8. On the premise of a given bit rate R, Side PSPNR and Central PSPNR can be decided by the codec at the same time, where Side PSPNR and Central PSPNR denote the measure quality when one description is lost and two descriptions are received, respectively.

Our method is compared with MDLTPC and MDROQ for the image boat, goldhill, couple, peppers, lena and baboon, the results are showed in **Fig. 6**, where the total bit rate (R) is 0.5 bpp. Similar, **Fig. 7** compare the proposed method with MDLTPC and MDROQ, where R is 1 bpp. It can be seen that for the given same Central PSPNR, the Side PSPNR of JND MDLTPC and JND MDROQ outperform MDLTPC, PMDROQ in most case, respectively.

Fig. 8 and **Fig. 9** show the optimal expected PSPNR of proposed method with others at $R = 0.5$ bpp and $R = 1$ bpp for two descriptions respectively, where loss probability $p = 0.1$. **Fig. 10** and **Fig. 11** at $R = 0.5$ bpp and $R = 1$ bpp for two descriptions respectively, where loss probability $p = 0.2$. Clearly, our method achieves obvious improvement at a certain Central PSPNR. Besides, on the premise of a given p, we can adjust the stepsize to change the values of Side PSPNR and Central PSPNR, and then get the maximum value of Excepted PSPNR. For example, when $R = 0.5$ bpp and $p = 0.1$, setting the value of Central PSPNR to 36.15 dB, and Excepted PSPNR will be close to the optimal value for lena.

From **Fig. 6-Fig. 11**, it can be clearly seen that after joining the JND, our method works better in the same number of observations, and we further validate the view that JND is claimed to match with human visual system accurately. Our method not only solves the problem of packet loss but also improves the coding efficiency.

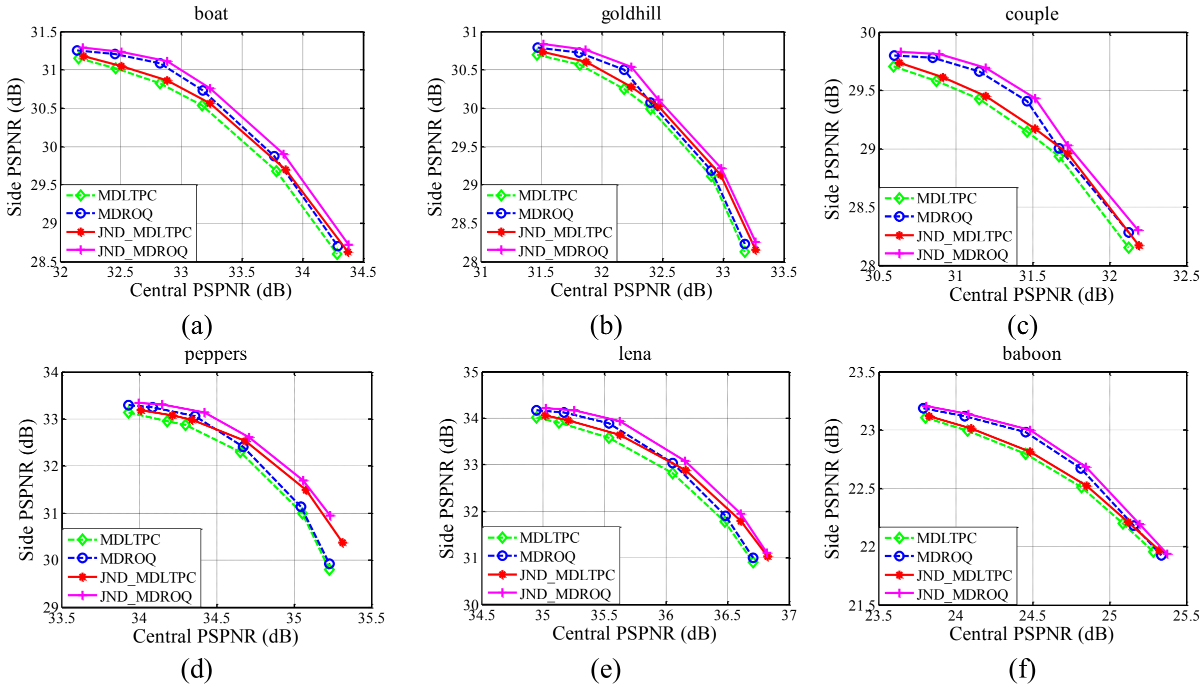

Fig. 6. Side decoder results with total rate 0.5 bpp.

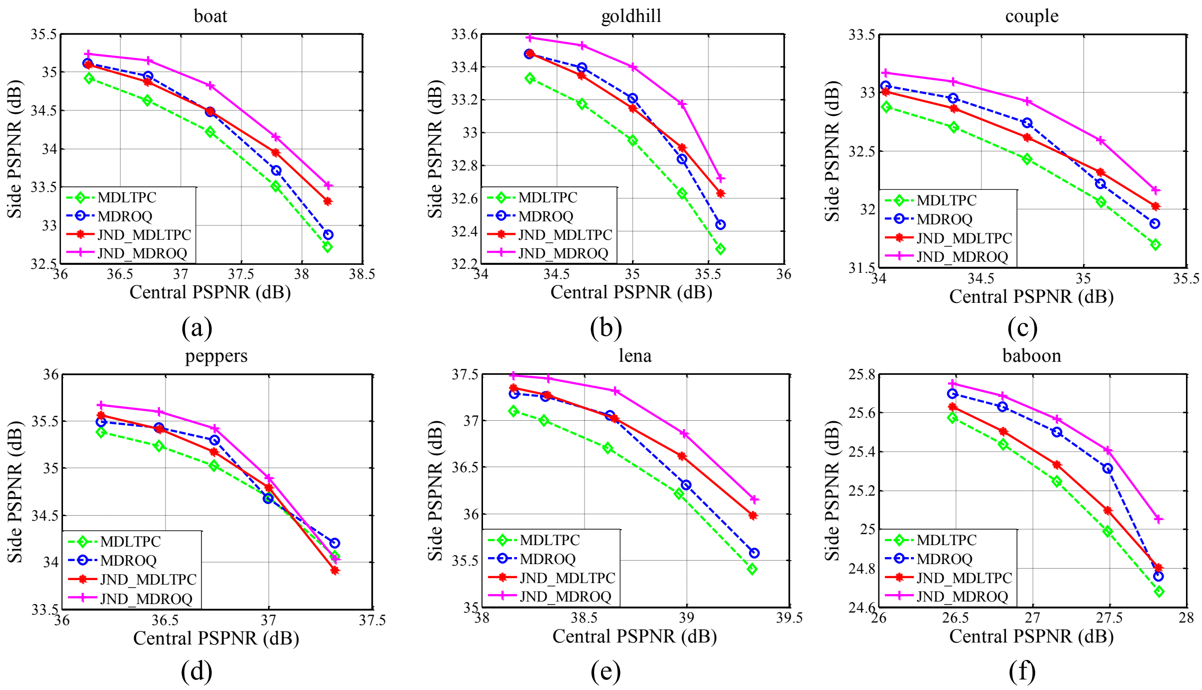

Fig. 7. Side decoder results with total rate 1 bpp.

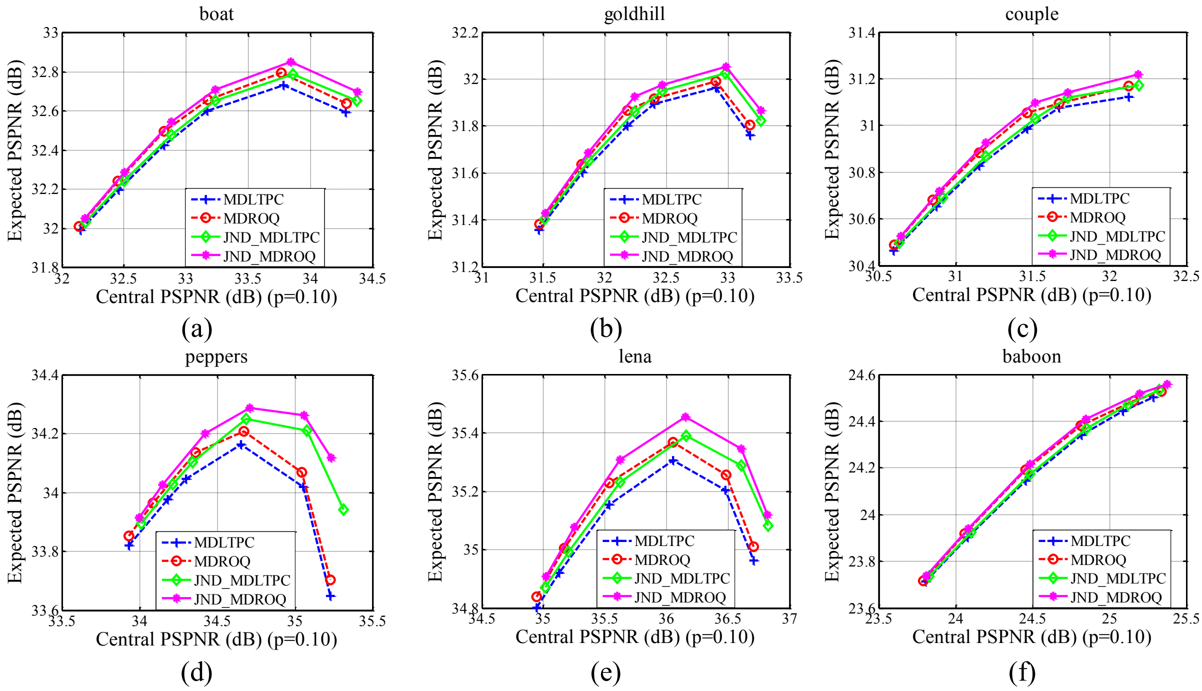

Fig. 8. The expected PSPNR with total rate 0.5 bpp.(p=0.10)

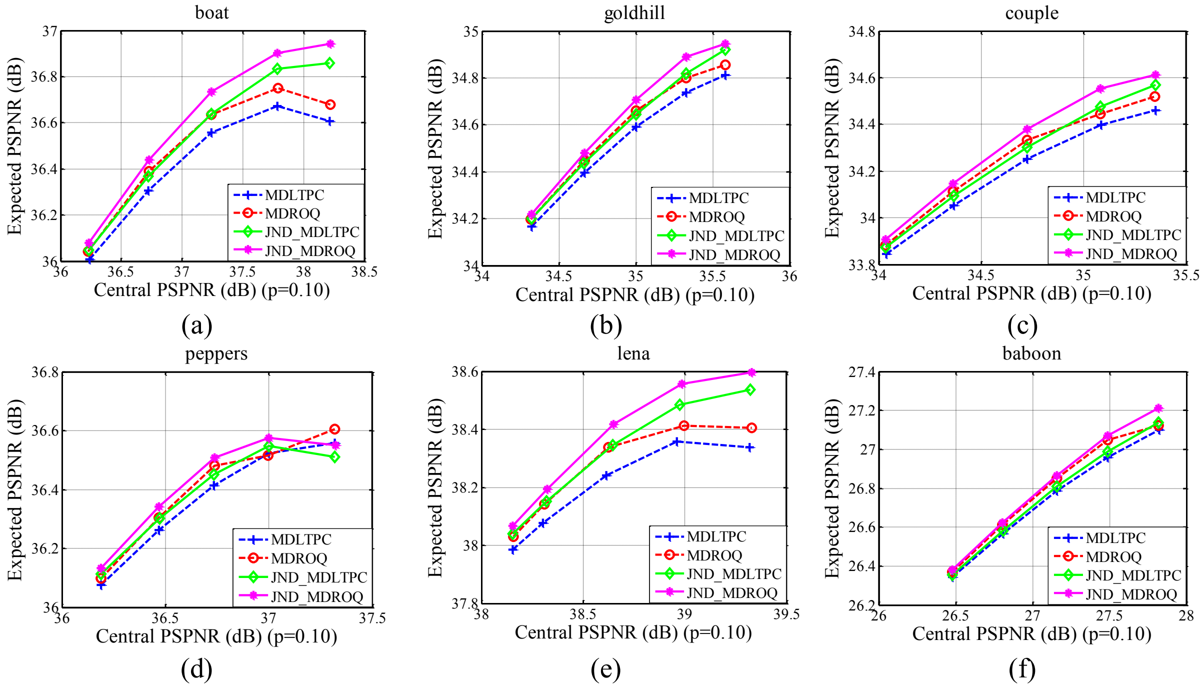

Fig. 9. The expected PSPNR with total rate 1 bpp.(p=0.10)

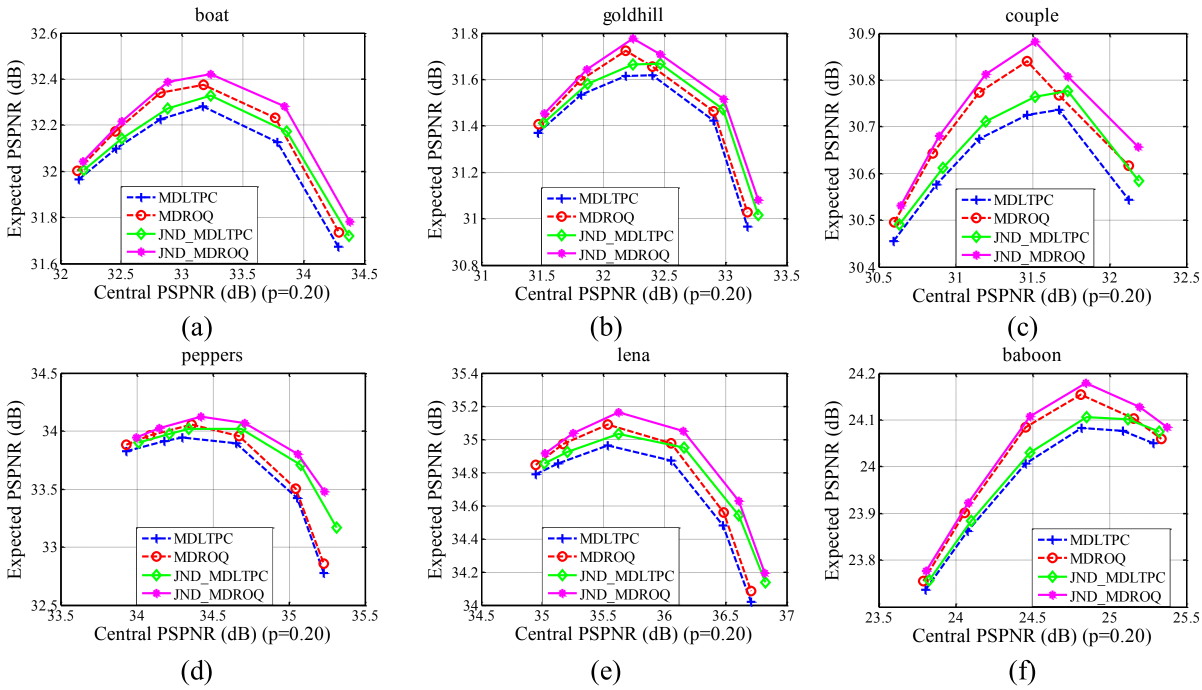

Fig. 10. The expected PSPNR with total rate 0.5 bpp.(p=0.20)

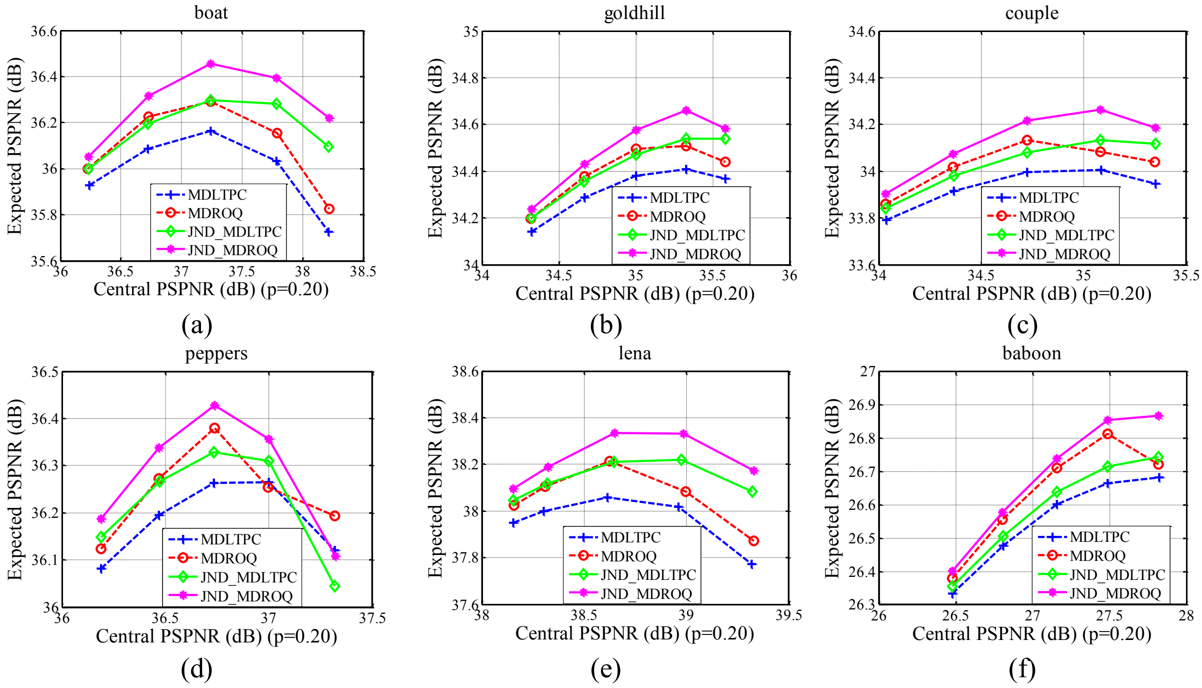

Fig. 11. The expected PSPNR with total rate 1 bpp. (p=0.20)

(a) MDLTPC (31.364dB) (b) MDROQ (31.416 dB) (e) MDLTPC (24.681 dB) (f) MDROQ (24.757 dB)

(c) JND_MDLTPC (31.798 dB) (d) JND_MDROQ (31.941 dB) (g) JND_MDLTPC (24.802 dB) (h) JND_MDROQ (25.053 dB)

Fig. 12. Side decoder results with total rate 0.5 bpp and Central PSPNR 36.306dB in (a)-(d), 1 bpp and 27.820 dB in (e)-(h). The Side PSPNR is included in the parentheses.

Fig. 12 shows some decoding results under the condition of one description received. The four methods are compared at the same Central PSPNR and total bit rate. Clearly, compared to previous MDC methods, JND based MDC methods achieve significant improvement in Side PSPNR. The Central PSPNR is fixed at about 36.606 dB, with R=0.5 bpp for lena. The

JND_MDLTPC and JND_MDROQ are 0.434 dB and 0.558 dB better than MDLTPC and MDROQ respectively. Similarly, the Central PSPNR is fixed at about 37.820 dB, with R=1 bpp for baboon. The JND_MDLTPC and JND_MDROQ are 0.121 dB and 0.296 dB better than MDLTPC and MDROQ respectively.

5. Conclusion

This paper proposed a novel multiple description image coding scheme, called JND-based multiple description image coding. The new scheme is based on the characteristics of the human visual model. The human eye can only perceive the change of the specific thresholds, which are named just noticeable difference (JND) thresholds. Due to the inherent characteristics of human vision, only the data that is greater than the corresponding JND threshold value is retained at the encoder. This paper calculates the DCT coefficients firstly, and then those coefficients are compared with the JND thresholds. The data that is less than the JND thresholds can be neglected, which can improve the coding efficiency. The image coding results of the proposed method outperforms other existing methods.

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