Impact of Dead Zone Size on the Rate/Distortion Performance of Wavelet-Based Perceptual Image Encoders

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***Abstract*— When using uniform quantization schemas with dead zone, the final R/D performance may be affected by two parameters, (a) the dead zone size, and (b) reconstruction point location inside each quantization step. In this work we analyze how the dead zone size affects the image quality for wavelet based encoders that have been perceptually enhanced by using the Contrast Sensitivity Function (CSF). Since the application of CSF may change the distribution of wavelet coefficients in each quantization step, and particularly in the dead zone surroundings, choosing appropriate values for both quantization parameters, dead zone size and reconstruction point, may introduce benefits in terms of R/D performance. After a thorough study about the effects of both parameters, we observed that tuning a variable dead zone quantizer with optimum dead zone and reconstruction point values, rate savings up to 7.7% can be obtained when comparing with popular uniform or fixed dead zone quantizers.**

Keywords- perceptual quantization; image perceptual coding; rate distortion performace analysis; contrast sensitivity function, wavelet image encoders.

I. INTRODUCTION

In a lossy image or video encoder, the quantizer is the stage where the loss of information occurs. Obviously the loss of information is closely related with the loss of reconstruction quality and with the desired bit rate. The quantizer, as one of the most important stages of the encoder design, must be carefully designed to obtain the best possible image quality at a desired bit rate, or to get the lowest bit rate for a desired quality of the reconstructed image, i.e. it should be designed to obtain the best rate-distortion (R/D) relationship.

The most widely used quantization schemas used in coding standards are: (a) the Uniform Scalar Quantizer (USQ) used for example in the JPEG, SPITH, MPEG-2, MPEG-4 and JPEG 2000 Part I, among others, (b) the Uniform Scalar Dead Zone Quantizer (USDZQ) used in H.263, H.264/AVC and HEVC encoders, (c) the Universal Coded Trellis Quantizer (UTCQ) used in JPEG2000 Part II and finally (d) the Uniform Variable Dead Zone Quantizer (UVDZQ) that is also used in JPEG 2000 part II.

All these quantization schemas completely remove the image information carried by the coefficients located in the quantization interval around zero, known as the Dead Zone (DZ). The difference between USQ and USDZQ is the Dead Zone Size (DZS) as shown in Fig. 1, where the quantizer step size Δ remains constant or uniform. Also, in those quantizers, the location of reconstruction point is placed just at the center of the interval defined by each quantization step. For example, in Fig. 1, the reconstruction point for every wavelet coefficient which value falls in the first quantization step (between d1 and d2) is r1.

A parametrized UVDZQ can be used to act as a USQ or as a USDZQ quantizer. A UVDZQ can be modeled using the DZS, the step size Δ and the location of the reconstruction point that we denote as δ. The DZS use to be expressed as multiple of Δ, so, the USQ has a DZS of 1Δ and the USDZQ typically has a fixed DZS of 2Δ.

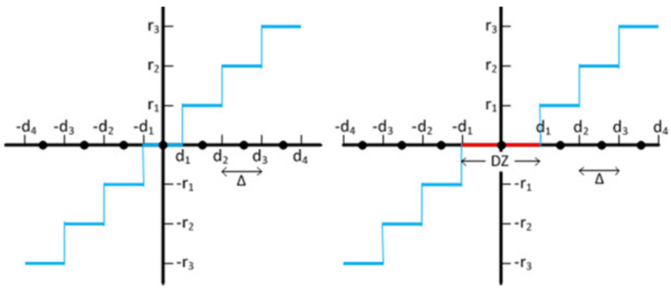

Figure 1. Uniform quantization schemas. Left USQ: DZS=1Δ; Right USDZQ: DZS=2Δ

To determine which coefficients should be set to cero, i.e. fully quantized, a tradeoff between quality and rate is needed. Variations in the DZS and in Δ have influence in the final quality and rate. Variations in δ will affect only to the final quality of the image, but not to the rate, as this parameter is used at the decoder side. Choosing the optimum combination of these three parameters to encode a single image, is a complex task, and even more if we need to find an estimation of these parameters that reasonably obtains similar results for every source image. This is the main motivation of this paper, to study and analyze the role of dead zone and reconstruction point parameters in the R/D performance of perceptual wavelet image encoders.

Other works in the literature have proposed and analyzed the design of different uniform scalar quantization. In [1] authors compared the performance of USQ, USDZQ and

UTCQ schemas with a wavelet based encoder that is not perceptually enhanced. Their results show that, although reconstruction errors are lower with the UTCQ, when combined with zero or high order entropy coders, the USDZQ was the best option with a careful selection of the DZS. The results show that the USDZQ can effectively reduce the output bits of the entropy coder. Therefore, authors showed that a parametrized USDZQ, i.e. a UVDZQ, is suitable for transform based image compression systems.

It is common in the literature, to use the center of the quantization interval to locate δ [2], or in some cases the centroid of the coefficient distribution in each quantizer interval. Nevertheless, there are other recommended positions to locate δ when using DCT based encoders and solutions [3].

Some works also analyze the importance of these parameters, specifically, the DZS and δ location. In the H.264/AVC standard a rounding parameter *f* is proposed to control the location of the reconstruction point inside each quantization step size, being f=Δ/3 for intra coding and f=Δ/6 for inter coding. In [4], authors apply a variable dead zone quantization scheme to the H.264/AVC using an offset parameter that modifies how the *f* parameter affects the DZS. Thus, the quantizer adjusts better the location of δ to the shape of the coefficient distribution inside the quantization intervals.

In [5] analytical studies were performed to obtain the optimum DZS for a specific bit rate range, up to 1 bpp. They propose an algorithm to obtain the optimum DZS and quantization step Δ. A dead zone quantizer, designed with those parameters minimizes the mean square error of the quantized source. The author uses a GGD (Generalized Gaussian Distribution) to test the algorithm with different types of coefficient distributions, as Gaussian, Laplacian and others with longer tails. In all cases, the author maintains δ at the center of the quantization step.

Also, in [2,6] Marcellin et al. showed the influence of the dead zone size in the R/D performance of the JPEG2000 encoder, using a variable dead zone quantization scheme. They also use a GGD tuned into Gausian, Laplacian and longer tail distributions, to cover the variability observed in the PDFs (Probability Density Functions) of wavelet coefficients in typical imaginery. Authors propose a DZS of 1.5Δ which can provide a very slight decrease in MSE and generate more visually pleasing low-level texture reconstruction. As there is no optimal δ for all images, the JPEG2000 standard allows the decoder free choice of δ, varying from 0 to 1, using δ=1/2 for the center of the interval as recommended value for most images.

As shown, the encoder performance can be increased using dead zone quantizers and adjusting the DZS. In [7] the author did an experiment with one single image and a wavelet based encoder to determine which DZS obtains the best performance. They measured the quality gain when replacing an USQ quantizer by an USDZQ in a DWT based encoder. The study was done in terms of R/D performance with the PSNR as quality metric. For that image an optimal DZS of 1.9Δ was obtained providing a quality increase of 0.5 dBs.

In the aforementioned studies, different uniform scalar quantizers were studied, highlighting the influence of both the DZS and the reconstruction point parameters in the R/D performance of wavelet-based encoders. As it can be observed, these studies (a) were carried with different testing conditions, proposing different optimum DZS, (b) suggest reconstruction points located at the center of the quantization intervals, and (c) do not consider perceptual quantization approaches.

In this work, we will perform a thorough study to determine how the DZS and δ parameters affect the R/D performance of a wavelet-based encoder that have been perceptually enhanced by using the Contrast Sensitivity Function (CSF).

When perceptual coding techniques are applied, as the inclusion or the CSF, the transformed coefficients are weighted conform to its perceptual importance. This can be accomplished in different ways as exposed in [8], but the main idea is to give more weight or importance to those coefficients located in the spatial frequencies for which our Human Visual System (HVS) is sensitive for.

The application of CSF changes the distribution of wavelet coefficients providing perceptual uniformity, so that when a uniform quantizer is applied it affects proportionally in the same way to all the coefficients. In order to maximize the R/D performance for a wide bit rate range, is important to choose an optimum relationship between the DZS and Δ and the best value of δ.

To determine the magnitude of the expected performance gains, we will use a UVDZQ inside a wavelet-based encoder that has been perceptually enhanced by using the CSF. We will cover a wide rate range, up to 3 bpp, i.e. from low quality up to the perceptually visually lossless quality threshold, by increasing the value of Δ. We will measure the performance using the PSNR-HVS quality metric since, as some studies suggest [9,10,11], performance comparisons of perceptually enhanced encoders should be done using perceptual Quality Assessment Metrics (QAM).

The rest of the paper is organized as follows: in section II a brief review of different quantization schemas and how they are related is presented. In section III the methods we have used in this work are presented. Section IV presents the results and finally, in section V, some conclusions and future work are exposed.

II. Quantization Schemas

In this section we briefly review the formulation for USQ, USDZQ and UVDZQ quantization schemas and how the UVDZQ quantizer may be considered a universal quantizer, being able to behave as an USQ or an USDZQ by properly tuning the quantization parameters.

Any quantizer can be decomposed into two distinct stages, referred to as the classification stage (or forward quantization stage) and the reconstruction stage (or inverse quantization stage). Equations (1) and (2) are the forward an inverse stages of a USQ. Equations (3) and (4) represent these stages for a USDZQ and finally (5) and (6) correspond to a UVDZQ.

$$C' = sign(C)\left\lfloor \frac{|C|}{\Delta} + \frac{1}{2} \right\rfloor \tag{1}$$

$$\hat{C} = \Delta\, C' \quad (2)$$

$$C' = sign(C)\left\lfloor \frac{|C|}{\Delta} \right\rfloor \quad (3)$$

$$\hat{C} = sign(C')(|C'| + \delta)\Delta \quad (4)$$

$$C' = \begin{cases} sign(C)\left\lfloor \frac{|C|+\xi\Delta}{\Delta} \right\rfloor & if\ |C| \geq -\xi\Delta \\ 0 & if\ |C| < -\xi\Delta \end{cases} \quad (5)$$

$$\hat{C} = \begin{cases} sign(C')(|C'| - \xi + \delta)\Delta & if\ C' \neq 0 \\ 0 & if\ C' = 0 \end{cases} \quad (6)$$

Where C is the transformed coefficient before quantization, C' is the quantized coefficient after the forward stage, and $\hat{C}$ is the recovered value after the inverse quantization stage. USQ recovers the coefficient value in the middle of the interval. The constant δ, used in the other schemas sets the location of the reconstruction value. Allowed values for δ are in the range $[0..1]$. ξ defines the size of the dead zone, allowed values are in the range $(-\infty..1]$. And finally, the quantization step size, Δ, determines the amount of quantization and therefore the desired compression level.

The ξ parameter ($\xi \leq 1$), determines the size of the dead zone in a UVDZQ. Depending on its value the dead zone size is set as follows:

- $\xi < 0$ increases the typical USDZQ dead zone, i.e. $DZS > 2\Delta$
- $\xi = 0$ produces a dead zone of $DZS = 2\Delta$, being Δ the first decision point or threshold (d_1 in Fig.1).
- $0 < \xi < 1$ reduces typical dead zone size, i.e. $DZS < 2\Delta$, where the corresponding value of a USQ is $\xi = 0.5$ which sets $DZS = 1\Delta$.
- As ξ approaches to 1 the DZS is reduced being 0 when ξ=1

In order to tune a UVDZQ to become an USQ we have to set $\xi = 0.5$ and δ=0.5, and to become a USDZQ with the reconstruction point at the middle of the quantization interval, this parameters must be set to $\xi = 0.0$ and δ=0.5.

III. Methods

As mentioned in the introduction section, the objective of this study is to analyze how the DZS and the location of δ affect to the R/D performance of perceptually enhanced wavelet based image encoders, specifically using the CSF approach as perceptual enhancement.

So, for this study we use the perceptual image encoder described in [12], and a perceptual QAM, specifically the PSNR-HVS [13], to measure the perceptual quality of each quantization scheme by means of the C++ implementation of the Video Quality Measurement Tool (VQMT) [14]. The encoder uses an optimized weighting matrix that follows one of the most widely used CSF models [15].

Variations of these two parameters, DZS and δ, produce different R/D performance. We analyze the R/D performance from two perspectives. The first one is the quality gain, i.e. to compare quality at the same bit rates, and the second one is the bit rate saving, i.e. to compare bit rates at the same reconstructed quality levels.

To provide a value of the rate savings and quality enhancements, we use the Bjontegaard method [16] to present the results expressed as percentage of gain for several rate and quality intervals, together with absolute rate values expressed in bits per pixel (bpp).

We have defined a training set of representative images conformed with the 23 images of the Kodak Set [16] (768x512). For each image of the training set, we will obtain the pair of parameters ξ and δ that maximizes the area of the R/D performance curve. To do that, we will create a 2D evaluation space of (ξ,δ) values with the ranges shown below to analyze the behavior of the UVDZQ . For each combination of these two parameters, we encode and decode the image for increasing values of the quantization step size Δ. We measure the quality in PSNR-HVS dBs and the rate in bpp.

- $-0.250 \leq \xi \leq 1$ Using steps of 0.010 ξ to get 126 different values. This range produces DZS varying from 2.5Δ to 0 in steps of -0.02Δ
- $0 \leq \delta \leq 1$ Using steps of 0.1 δ to get 11 different positions varying from left to right in the quantization interval.

We have computed a total of 1386 (ξ,δ) combinations. For each one we build a R/D curve with 13 different Δ evenly distributed. This produces a total of 18018 compressed images for each of the 23 images in the training set.

Fig. 2 shows the R/D behavior for the image '01' of the training set. Each curve corresponds to one of the ξ values inside the evaluation range, but only the curve with the best performing δ parameter is plotted. The curve with the best performing (ξ,δ) combination, is highlighted with a thicker line. We choose a wide range of ξ values to avoid local maximums for the curve areas and to have a wide sight of the R/D performance behavior.

We measure the area of each of these curves over the rate axis and this way for each image we can obtain the (ξ,δ) pair that maximizes the area. That curve has the best R/D behavior in the covered rate range.

The rate range under study goes from 0 to 3.0 bpp for every image in the set. The quality, expressed in PSNR-HVS dBs, varies, for the whole set, from 17.3 dBs to 57.7 dBs, i.e. from very bad quality respect the original image up to visually lossless. The dynamic quality range of each image varies, depending on its content.

For each image, we choose the best performing (ξ,δ) quantization parameters that provide us with the optimum R/D performance curve. We call this curve as C_{OPT} and then we compare it with the curves corresponding to the USQ and UDZQ parameters, called C_{USQ} and C_{UDZQ} with (ξ=0.5,δ=0.5) and (ξ=0.0,δ=0.5) respectively. In this comparison we measure the gain in rate and quality of C_{OPT} with respect C_{USQ} and C_{USDZQ} using the Bjontegaard method.

We analyze these differences for the whole bit rate range and also for rate ranges corresponding to low, mid, high and very high bit rates. Table I shows these rate ranges with an approximation of their corresponding quality intervals. The rate ranges are: ALL which stands for the whole-range, L for low-rate, M for medium-rate, H for high-rate and VH stands for very-high-rate. Depending on the image content, the compression rate is different for each image, therefore columns for quality in Table I show the average of the low and high quality limits of all images in the training set.

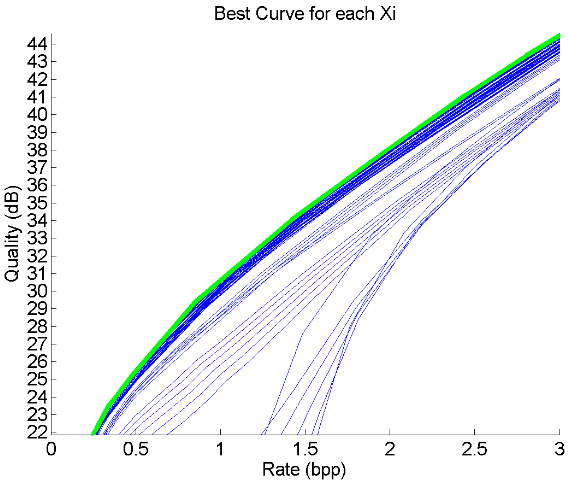

Figure 2. Best Rate/Distortion behavior for each ξ in the set. In this figure, only the best δ is shown for each ξ.

For each of these rate ranges, the gain in quality or rate for C_{OPT} with respect to C_{USQ} and C_{UDZQ} is calculated. So, we get the maximum gain for each image and rate range in the training set, with respect to the other quantization schemas. The average gain for the training set in each rate range is also provided in the results section.

The C_{OPT}, C_{USQ} and C_{UDZQ} curves have been processed with an automatic curve fitting process that searches for the best fitting, using polynomial and rational models provided by the Matlab curve fitting toolbox. Once we have the parameters that fit the curves, we can obtain the absolute difference in rate and quality for any range. We can also obtain the averaged absolute bit rate savings expressed in bpp, for all the images in training set.

After analyzing the training set, we will use a new image test set composed by the following images at different resolutions: (512 x 512): Balloon, Barbara, Boat, Goldhill, Horse, Lena, Mandrill and Zelda; (2048 x 2560): Bike, Cafe and Woman. As the optimum (ξ,δ) pair is different for each image, we get a representative sub-optimum (ξ,δ) pair based on the ones found with the training set.

IV. RESULTS

Table II shows the best working parameters pair, i.e. the optimum (ξ,δ) pair, for each image in the training set. As we can see, the δ parameter, that fixes the location of the recovering point, remains almost constant close to the center of the quantization interval (δ = 0.44). On the other hand, the optimum ξ value varies in a range from 0.30 to 0.49 units, which corresponds to dead zone sizes of 1.02Δ to 1.40Δ.

As mentioned before, lower ξ values produce higher DZS, so, in Table II, we can see that for the lowest ξ (0.30) we get the wider DZ, 1.40Δ. For the whole training set we get an average DZS of 1.19Δ, which corresponds to a dead zone size 19% wider than the one for a USQ quantizer and 40.5% narrower than the one for a UDZQ. Therefore, a first conclusion is that as the optimum DZS is closer to a USQ quantization scheme than to a USDZQ one, i.e. a USQ quantizer should provide better R/D behavior than a USDZQ.

TABLE I. RATE RANGES UNDER STUDY

Rate Ranges	Rate (bpp)		Quality (dB)	
	Low	high	low	high
ALL	0.0	3.0	25.0	50.5
L	0.0	0.5	25.0	32.1
M	0.5	1.0	32.1	37.6
H	1.0	1.5	37.6	41.7
VH	1.5	3.0	41.7	50.5

TABLE II. OPTIMUM ξ AND δ FOR THE TRAINING SET

Image	Optimum ξ	Optimum δ	DZS
1	0.460	0.4	1.08 Δ
2	0.400	0.4	1.20 Δ
3	0.300	0.5	1.40 Δ
4	0.450	0.4	1.10 Δ
5	0.450	0.5	1.10 Δ
6	0.390	0.5	1.22 Δ
7	0.350	0.5	1.30 Δ
8	0.390	0.5	1.22 Δ
9	0.380	0.4	1.24 Δ
10	0.400	0.4	1.20 Δ
11	0.380	0.5	1.24 Δ
12	0.450	0.4	1.10 Δ
13	0.450	0.4	1.10 Δ
14	0.490	0.4	1.02 Δ
15	0.380	0.4	1.24 Δ
16	0.370	0.5	1.26 Δ
17	0.400	0.4	1.20 Δ
18	0.450	0.4	1.10 Δ
19	0.350	0.5	1.30 Δ
20	0.350	0.5	1.30 Δ
21	0.380	0.5	1.24 Δ
22	0.460	0.4	1.08 Δ
23	0.380	0.4	1.24 Δ
Min(ξ,δ)	0.300	0.40	1.40 Δ
Mean(ξ,δ)	0.403	0.44	1.19 Δ
Max(ξ,δ)	0.490	0.50	1.02 Δ

As the results depend on the image content, we show the average and maximum values for the training set. Table III shows the average quality gains and relative rate savings for all images in the training set, while Table IV shows the corresponding maximum gains. As shown, with the optimized UVDZQ up to 6.64% of rate saving in the L rate range and 7.67% in the M rate range can be obtained. Regarding quality, maximum quality increases of 0.41 dBs and 0.60 dBs in the L and M rate ranges respectively can be obtained.

Fig. 3 shows the comparison of the R/D curves for image '*01*' of the training set considering the bit rate range from 0 to 1.5 bpp, (rate ranges L, M, and H). As shown, the bit rate saving holds for all the bit rate ranges. Fig. 4 focuses only the R/D comparison in the H rate range, in this case for image '14' from the training set. An absolute quality gain of 0.6 dBs is obtained when using the optimum settings with respect to the use of the USDZQ scheme. This corresponds to a rate saving of 5.9%.

TABLE III. AVERAGE RESULTS FOR TRAINING SET.

Rate Ranges	Quality Gain (dB)		% of Rate Saving	
	USQ	**UDZQ**	**USQ**	**UDZQ**
ALL	0.15	0.36	1.48	3.31
L	0.12	0.25	2.01	4.12
M	0.12	0.32	1.55	3.96
H	0.17	0.38	1.74	3.76
VH	0.17	0.40	1.38	2.96

TABLE IV. MAXIMUM GAINS FOR TARINING SET.

Rate Ranges	Quality Gain (dB)		% of Rate Saving	
	USQ	**UDZQ**	**USQ**	**UDZQ**
ALL	0,30	0,53	3,23	4,55
L	0,26	0,41	5,30	6,64
M	0,25	0,60	3,53	7,67
H	0,34	0,60	4,54	5,92
VH	0,35	0,59	3,07	4,27

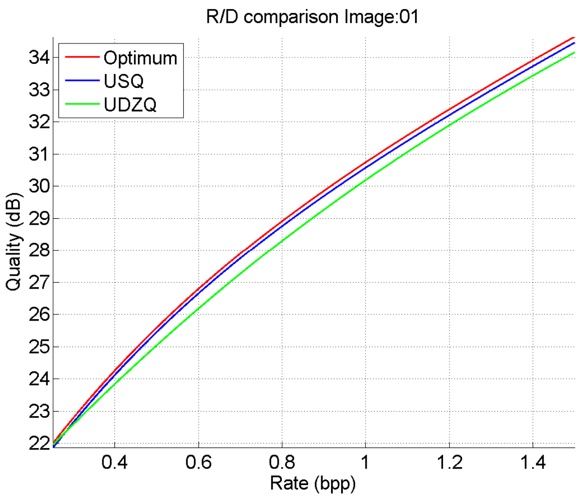

Figure 3. R/D Comparison between the optimum quantizer settings, USQ and USDZQ, for image '01' and for the L, M and H rate ranges.

Now, we will proceed to evaluate the R/D performance of the optimized UVDZQ with the images of the test set. As we described before, we need to compute its corresponding optimum parameter pair. However, to be applied in practice to a single image, we propose a single approach by taking the centroid of optimum DSZ and δ values obtained for each image of the training set (see Table II). The resulting parameter pair estimation $(\widehat{DSZ,\delta})$ will be used for the images in the test set.

Using this simple approach we evaluate USQ, USDZQ, and the optimized UVDZQ with the estimated parameter pair $(\widehat{DSZ,\delta})$ using the images in the test set. In Table V we show the average of the quality gains and rate savings of all images in the test set. As it can be shown, we obtain similar results of quality gain and rate savings than the ones obtained with the training set. In particular, we can obtain up to 4.02% of bit rate saving in the M rate range for 512x512 image resolution and up to 4.53% of rate saving in the M bit rate range for 2048x2560 image resolution.

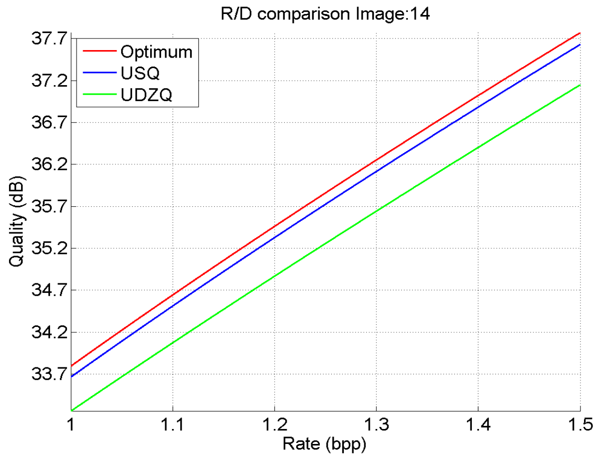

Figure 4. R/D Comparison between the optimum quantizer settings, USQ and USDZQ, for image '14' at the H rate range.

In Table VI we show particular results at different compression rate ranges. The optimized UVDZQ gets up to 5.14% of rate saving with the goldhill image at rate range H, and 5.68% with the cafe image at M Range. It also improves the perceptual performance up to 0.54 PSNR-HVS dBs for some images.

TABLE V. AVERAGE RESULTS FOR TEST SET. PSNR-HVS dBs FOR QUALITY AND % OF RATE SAVING FOR RATE.

Rate Ranges	Quality Gain (dB)		% of Rate Saving	
	USQ	**USDZQ**	**USQ**	**USDZQ**
512 x 512				
ALL	0.22	0.34	2.17	3.28
L	0.17	0.17	2.90	3.02
M	0.16	0.32	2.17	**4.02**
H	0.23	0.36	2.52	3.69
VH	0.25	0.38	2.02	3.00
2048 x 2560				
ALL	0.16	0.41	1.43	3.62
L	0.08	0.25	1.29	3.97
M	0.11	0.40	1.30	**4.53**
H	0.15	0.40	1.48	3.75
VH	0.19	0.45	1.45	3.36

TABLE VI. ABSOLUTE RESULTS FOR SOME RATE RANGES IN THE TEST SET. PSNR-HVS dBs FOR QUALITY AND % OF RATE SAVING FOR RATE.

Img. Size	Image	Quality Gain (dB)		% of Rate Saving	
		USQ	**USDZQ**	**USQ**	**USDZQ**
Rate Range: H (1.0 to 1.5 bpp)					
512x512	balloon	0.25	0.31	2.25	2.70
	barbara	0.15	0.36	1.41	3.43
	boat	0.15	**0.54**	1.36	5.10
	goldhill	0.13	0.47	1.43	**5.14**
	horse	0.26	0.41	2.59	4.08
	lena	0.32	0.23	4.04	2.97
	mandrill	0.31	0.39	3.30	4.11
	zelda	0.27	0.14	3.79	1.98
Rate Range: M (0.5 to 1.0 bpp)					
2048x2560	bike	0.16	0.28	1.83	3.18
	cafe	0.05	**0.54**	0.46	**5.68**
	woman	0.13	0.39	1.61	**4.73**
Rate Range: L (0.0 to 0.5 bpp)					
2048x2560	bike	0.08	0.18	1.15	2.75
	cafe	0.04	0.29	0.71	**4.55**
	woman	0.12	0.29	2.01	**4.60**

I. CONCLUSIONS AND FUTURE WORK

In this work we have used a UVDZQ to analyze how the values of dead zone size and the location of reconstruction point, impact on the R/D performance of a perceptual enhanced wavelet encoder. From this study, we noticed that each image has a different optimum quantizer parameters (ξ,δ) pair, for which the R/D performance is maximized. This optimum parameter pair is searched in a way that maximizes the R/D performance for a wide rate range, from 0 bpp to 3 bpp.

In order to quantify the benefits of using the optimum parameter pair, the R/D performance of the resulting UVDZQ quantizer is compared with the USQ and USDZQ quantizers, as they are the most commonly used quantization schemas in image compression. Results show that, up to a 4.55% and 3.23% of average rate savings in the whole rate range may be obtained when comparing with the USDZQ and the USQ, respectively. However, as the R/D curve has a nonlinear behavior, the optimum UVDZQ, can obtain higher rate savings: 6.64 % with respect USDZQ and 5.30% with respect USQ in the range for 0 to 0.5 bpp and 7.67% and 3.53%, respectively, in the range from 0.5 to 1.0 bpp.

The USQ scheme performs better than the USDZQ scheme because its dead zone size is closer to the optimum we found for each image in both training and testing sets and for all rate ranges. In other words, a dead zone size of 1Δ performs better than one of 2Δ when transformed coefficients have been perceptually weighted with a CSF weighting matrix. The CSF gives to each quantized coefficient the correct perceptual weight so that a simple uniform quantization affects in the same perceptual proportion to all of them.

With the performance results obtained, we can assure that the use of an optimized UVDZQ quantizer will improve the overall R/D performance of a perceptual enhanced wavelet encoder. However, to be applied in practice to a single image, we need its corresponding optimum parameter pair. We propose a simple approach by taking the centroid of DZS and δ values obtained from images in training set as the sub-optimum parameter pair to be used for other images.

Results show that even with this sub-optimum value, good R/D performance is obtained for a variety of images. The UVDZQ gets up to 5.68% and 4.73% of rate savings with respect to the USDZQ for the cafe and woman images, respectively in the rate range from 0.5 to 1.0 bpp., or 4.5% and 4.6% respectively in the range from 0 to 0.5 bpp.

Although more research must be done to obtain a better estimator of the optimum quantizer parameters for a single image, the results obtained with the naive approach are good enough and close to the ones obtained by the optimum quantizer.

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REFERENCES

[1] Jinhua Yu, "Advantages of uniform scalar dead-zone quantization in image coding system," Communications, Circuits and Systems, 2004. ICCCAS 2004. 2004 Int. Conference on, 2004, pp. 805-808 Vol.2.

[2] Michael W. Marcellin, Margaret A. Lepley, Ali Bilgin, Thomas J. Flohr, Troy T. Chinen, and James H. Kasner. “An overview of quantization in JPEG2000” . Signal Processing: Image Communication, 17:73–84, 2002

[3] S. Notebaert, J. De Cock, K. Vermeirsch, P. Lambert and R. Van de Walle, "Leveraging the quantization offset for improved requantization transcoding of H.264/AVC video," Picture Coding Symposium, 2009. PCS 2009, Chicago, IL, 2009, pp. 1-4

[4] T. Wedi and S. Wittmann, "Quantization offsets for video coding," 2005 IEEE Int. Symposium on Circuits and Systems, 2005, 324-327 Vol. 1.

[5] Bo Tao, "On optimal entropy-constrained deadzone quantization," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 11, no. 4, pp. 560-563, Apr 2001.

[6] Michael W Marcellin. “JPEG2000: image compression fundamentals, standards, and practice”, volume 1. springer, 2002

[7] Jacob Ström. “Dead zone quantization in wavelet image compression” - mini project in ece 253a, 1996.

[8] Marcus J. Nadenau, Julien Reichel, and Murat Kunt. “Wavelet-based color image compression: Exploiting the contrast sensitivity function.” IEEE Transactions on image processing, 12(1), 2003.

[9] M. Martinez-Rach, O. Lopez, P. Piñol, J. Oliver, and M. Malumbres, “A study of objective quality assessment metrics for video codec design and evaluation,” in Eight IEEE International Symposium on Multimedia, vol. 1, ISBN 0-7695-2746-9. San Diego, California: IEEE Computer Society, Dec 2006, pp. 517–524

[10] H. R. Sheikh, M. F. Sabir, and A. C. Bovik, “A statistical evaluation of recent full reference image quality assessment algorithms,” IEEE Trans. on Image Processing, vol. 15, no. 11, pp. 3440– 3451, 2006.

[11] Z. Wang, A. Bovik, H. Sheikh, and E. P. Simoncelli, “Image quality assessment: From error visibility to structural similarity,” IEEE Transactions on Image Processing, vol. 13, no. 4, 2004.

[12] Martinez-Rach, Miguel Onofre. “Perceptual image coding for wavelet based encoders”. PhD thesis, Universidad Miguel Hernández. http://hdl.handle.net/11000/1764 December 2014.

[13] Egiazarian, K., Astola, J., Ponomarenko, N., Lukin, V., Battisti, F., & Carli, M. (2006, January). New full-reference quality metrics based on HVS. In CD-ROM proceedings of the second international workshop on video processing and quality metrics, Scottsdale, USA (Vol. 4).

[14] Multimedia Video Processing Group, “VQMT: Video Quality Measurement Tool”, http://mmspg.epfl.ch/vqmt

[15] J. Mannos and D. Sakrison, “The effects of a visual fidelity criterion of the encoding of images,” IEEE Transactions on Information Theory, vol. 20, no. 4, pp. 525 – 536, Jul. 1974.

[16] G. Bjontegaard. “Calculation of average psnr differences between rdcurves (vceg-m33)”. Technical report, VCEG Meeting (ITU-T SG16 Q.6), Austin, Texas, USA, April 2001.