Influence of Dead Zone quantization parameters in the R/D Performance of Wavelet-Based Image Encoders

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Abstract: Uniform quantization schemas with dead zone are commonly used in image and video codecs. The design of these quantizers affects to the final R/D performance, being two of the quantizer parameters, the responsible for that variations: (a) the dead zone size and (b) the reconstruction point location inside each quantization step. We analyze how variations of these parameters, by means of a variable dead zone quantizer, affect to the R/D performance of wavelet-based image encoders, using three different quality metrics. We tune the quantizer for each image to obtain the optimum parameters that provide the best R/D behavior for each of the metrics for different rate ranges, without altering the rest of the encoder stages. We provide a general parameter set for each metric and rate range, to be used with other images to obtain important rate savings and better quality values for each of metrics.

1. Introduction

The reconstruction quality of image or video encoders are influenced by many design factors of the encoder and decoder, but the most important factor is the loss of information produced in the quantization stage. In that stage the loss of information is used to obtain an image or video at a desired target bit rate, therefore the design of the quantizer must be carefully done in order to preserve the image information in such a way that the best possible image quality is obtained for that target bit rate. In other words, the quantizer should be designed to obtain the best rate-distortion (R/D) relationship.

The most widely used quantization schemas used in coding standards are:

- The Uniform Scalar Quantizer (USQ) used for example in the JPEG, SPITH, MPEG-2, MPEG-4 and JPEG 2000 Part I, among others,
- The Uniform Scalar Dead Zone Quantizer (USDZQ) used in H.263, H.264/AVC and HEVC encoders,
- The Universal Coded Trellis Quantizer (UTCQ) used in JPEG2000 Part II
- The Uniform Variable Dead Zone Quantizer (UVDZQ) that is also used in JPEG 2000 part II.

These quantization schemas remove the image information of those transformed coefficients that are located in the interval around zero, known as the Dead Zone (DZ). In Fig. 1 we can see that the difference between USQ and USDZQ quantizers is the Dead Zone Size (DZS), while the quantizer step size Δ remains constant or uniform in both quantizers. In Fig. 1 the reconstruction point is also represented with a black dot just at the center of each quantization interval. For example, all the coefficient values between d_1 and

d_2 that in the quantization stage are encoded with a value of r_1, at the decoder side, in the dequantization stage, its reconstructed value will be the midpoint between d_1 and d_2. The location of this point does not alter the size of the encoded bitstream but has an influence in the reconstructed quality of the image or video.

A parametrized UVDZQ can be used to act as a USQ or as a USDZQ. The parameters that model the resulting quantizer are: (1) The dead zone size (DZS), (2) the step size Δ and (3) the location of the reconstruction point that we denote as δ.

The dead zone size is typically expressed as multiple of Δ (the quantization step size), i.e. an USQ quantizer has a DZS of 1Δ, meanwhile an regular USDZQ quantizer has a fixed DZS of 2Δ.

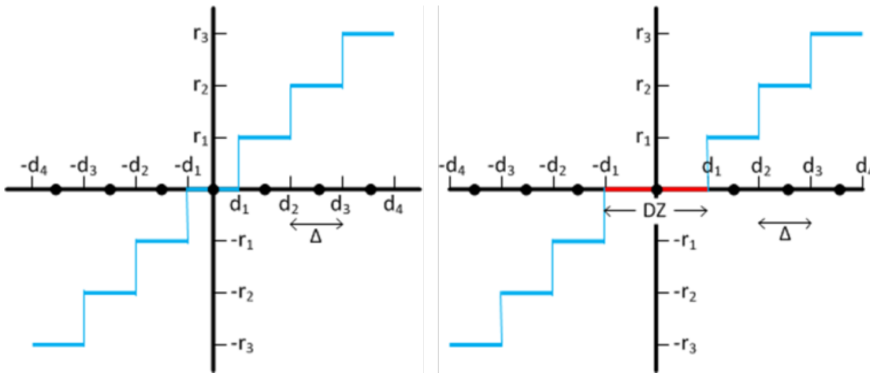

Figure 1: Uniform quantization schemas.
Left USQ: DZS=1Δ; Right USDZQ: DZS=2Δ

The dead zone size determines the amount of coefficients that are fully quantized, i.e. set to zero. The value of these coefficients could not be recover in the dequantization stage, therefore the dead zone size should be carefully determined and normally a tradeoff between quality an rate is needed. The DZS has influence in the final bit rate and quality but the location of the reconstruction point, the δ parameter, has influence only in the final quality. Choosing the optimum combination of these two parameters for a specific image is a complex task and even more to provide a general or estimated optimum that could be use with any other image to provide reasonably good results in terms of R/D. 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 wavelet-based 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. 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 hits 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 $f=\Delta/3$ for intra coding and $f=\Delta/6$ 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 Gaussian, 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. 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 the use of perceptual quality metrics to analyze the optimum quantization parameter to be used with these metrics.

In this work, we will perform a thorough study to determine how the DZS and δ parameters affect to the R/D performance of a wavelet-based encoder, analyzing the optimum quantizer parameter sets for a training image set, in order to provide a general quantizer parameter set to be used with three different quality metrics and for different rate ranges.

To determine the magnitude of the expected performance gains, we will use a UVDZQ in a wavelet-based encoder without altering the rest of the encoder or decoder states. 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 and providing results for different rate ranges. We will measure the performance using the PSNR, MSSSIM and PSNR-HVS quality metrics.

The rest of the paper is organized as follows: in section 2 a brief review of the analyzed quantization schemas and how they are related is presented. In section 3, the methods we have used in this work are explained. In section 4 the results of our study are exposed and finally, in section 5 some conclusions are provided.

2. 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 USQ forward an inverse stages. Equations (3) and (4) represent the ones for a USDZQ, and finally (5) and (6) correspond to a UVDZQ.

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

$$\widehat{\boldsymbol{C}} = \Delta\, \boldsymbol{C'} \qquad (2)$$

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

$$\widehat{\boldsymbol{C}} = \boldsymbol{sign}(\boldsymbol{C'})(|\boldsymbol{C'}| + \boldsymbol{\delta})\Delta \qquad (4)$$

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

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

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 (-∞..1]. And finally, the quantization step size, Δ, determines the amount of quantization and therefore the desired compression level.

The ξ parameter ($\xi \leqslant 1$), 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>2Δ
- $\xi = 0$ sets a DZS to 2Δ, being Δ the first decision point or threshold (*d1* in Fig.1).
- $0 < \xi < 1$ reduces typical dead zone size, i.e. DZS<2Δ, where the corresponding value of a USQ is ξ=0.5 which sets DZS=1Δ.
- As ξ approaches to 1 the DZS is reduced being 0 when ξ=1

In order to tune a UVDZQ to act as an USQ we have to set ξ=0.5 and δ=0.5, and ξ=0.0 and δ=0.5 for a USDZQ with the reconstruction point at the center of the interval.

3. Methods and Results

In this study we use the wavelet-based image encoder described in [12] to encode and decode the images at different compression levels in order to get a R/D curve. For analyze the R/D behavior we use three distortion metrics, the traditional PSNR, and two perceptual Quality Assessment Metrics, the MSSSIM [13] and the PSNR-HVS [14]. We use the C++ metrics implementation of the Video Quality Measurement Tool [15].

We analyze the R/D performance using each one of the aforementioned metrics, i.e. for each image we analyze three R/D curves, each one corresponding to a different metric. Besides, this analysis is done from two perspectives. The first one is to measure the quality gain, i.e. to compare quality at the same bit rates, and the second one is to measure the bit rate saving, i.e. to compare bit rates at the same reconstructed quality levels for each metric.

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 based on the Kodak Set (a set of 23 images of 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 for each quality metric.

To do that, we created a 2D evaluation space of (ξ,δ) values with the ranges shown below to analyze the behavior of the UVDZQ. For each combination of the parameters, we encode and decode the image for increasing values of the quantization step size Δ. We measure the quality in dBs for the PSNR and the PSNR-HVS metrics and in MSSSIM quality units for that metric. In all cases the rate is measured in bit per pixels (bpp).

These are the ranges for ξ and δ, to compose the 2D evaluation space:

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

So, we have computed all the corresponding (ξ,δ) combinations and for each one we build three R/D curves (one for each quality metric) using different Δs evenly distributed in the working bitrate range.

We have established four rate ranges , that are: L for low-rate (0.0-0.5 bpp), M for medium-rate (0.5-1.0 bpp), H for high-rate (1.0-1.5 bpp) and VH stands for very-high-rate (1.5-3.0 bpp). By using the Bjontegaard method, we can choose the (ξ,δ) pair that maximizes that area in each rate range. So, for each rate range we obtain the (ξ,δ) pair that best R/D behavior achieves for each visual quality metric defined in this work.

Once we have found the optimum parameters (ξ,δ) of our UVDZQ quantizer, we proceed to compare it with USQ and UDZQ quantizers. The R/D curve for the optimum parameters is called C_{OPT} and is compared with the curves for 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.

The C_{OPT}, C_{USQ} and C_{UDZQ} curves have been processed with an automatic curve fitting process that searches for the best fitting for each metric, 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 differences in rate and quality for any range. We can also obtain the averaged absolute bit rate savings expressed in bpp, for all the images.

As each image has different optimum (ξ,δ) pair, we compute the centroid $\widehat{(\xi,\delta)}$of the optimum (ξ,δ) pairs from the image training set for each rate range. This value will be a naive estimation of the optimum quantization parameter to be used to encode a particular image.

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. To encode these images we will use the estimated quantization parameter pair $\widehat{(\xi,\delta)}$.

4. Results

Table 1 shows, for the L (0 to 0.5 bpp) rate range, the optimum (ξ,δ) pair, for each image of the training set . We show in three columns ,one for each quality metric, the ξ and δ quantizer parameters that best R/D performance provide. In column DZS we show the resulting dead zone sizes expressed as multiples of Δ. The last row in Table II show the average values of each column.

As mentioned before, lower ξ values produce higher DZS, so, in Table 1, we can see that for the lowest ξ (0.05) we get the wider DZS, 1.90Δ in image number 4. From the values in the L rate range the δ parameter, that fixes the location of the recovering point, remains almost constant slightly left to the center of the quantization interval, δ = 0.40 or δ = 0.44 depending on the metric. On the other hand, the optimum ξ value varies in a range from 0.05 to 0.40 units, which corresponds to dead zone sizes of 1.90Δ to 1.20Δ, i.e. up to 37% of DZS variability .

For a USQ quantizer the DZS is 1Δ, and for a USDZQ DZS is just 2Δ, so, if we focus on the averaged values from Table 1 we see that for the L rate range the optimum DZS is located almost in the middle of the DZS of both quantizers, except for the PSNR-HVS metric that is closer to USDZQ than to USQ. The same values in Table 1 are acquired for the rest of the rate ranges.

In Table 2 we show the average values for all metrics and rate ranges. As it can be seen, different behavior of quantization parameters may be observed. Focusing in PSNR metric, as bitrate grows the DZS decreases (from 1.56 Δ at L rate range to 1.31 Δ at VH rate range), keeping constant the value of δ parameter (δ = 0.4). The rest of metrics follow a similar behavior. The explanation is simple and straightforward since at higher rates, the information of high frequency wavelet coefficients (typically coefficients of low magnitude) have a great impact in the reconstructed image quality, so they should survive to quantization step. So, in order to get good R/D performance, the DZS should be significantly reduced.

Now, we compare the results in terms of rate savings and quality gain. First we use the optimum parameters for each image in the training set. So, in Table 3 we see the average rate savings and the average quality gain for all the images in the training set, and in Table 4 we provide the maximum rate savings and quality gains.

As shown in Table 3, with the optimized UVDZQ for the two lowest rate ranges up to 11.12 %, 5.60% and 10.66% of average rate savings can be obtained for PSNR, MSSSIM and PSNR-HVS respectively, being able to achieve up to 15.18%, 11,23%, and 16,35% , as shown in Table 4. Regarding to quality, average quality increases up to 0.68 dBs with a maximum of 1.12 dBs can be obtained for the H rate range and PSNR-HVS. The shape of the MSSSIM curves jointly with its narrow quality dynamic range gives very low quality gains (measure in MSSSIM quality units) that are in contrast with the percentage of rate savings obtained for the same rate ranges.

Training Set	PSNR			MSSSIM			PSNR-HVS		
Image Num.	ξ	δ	DZS	ξ	δ	DZS	ξ	δ	DZS
1	0.15	0.40	1.70 Δ	0.3	0.5	1.40 Δ	0.13	0.4	1.74 Δ
2	0.18	0.40	1.64 Δ	0.13	0.4	1.74 Δ	0.1	0.4	1.80 Δ
3	0.25	0.40	1.50 Δ	0.22	0.4	1.56 Δ	0.09	0.5	1.82 Δ
4	0.21	0.40	1.58 Δ	0.28	0.4	1.44 Δ	0.05	0.5	1.90 Δ
5	0.24	0.40	1.52 Δ	0.3	0.5	1.40 Δ	0.2	0.4	1.60 Δ
6	0.22	0.40	1.56 Δ	0.37	0.4	1.26 Δ	0.25	0.4	1.50 Δ
7	0.25	0.40	1.50 Δ	0.23	0.5	1.54 Δ	0.15	0.5	1.70 Δ
8	0.25	0.40	1.50 Δ	0.26	0.5	1.48 Δ	0.15	0.5	1.70 Δ
9	0.28	0.40	1.44 Δ	0.25	0.4	1.50 Δ	0.16	0.5	1.68 Δ
10	0.25	0.40	1.50 Δ	0.35	0.4	1.30 Δ	0.08	0.5	1.84 Δ
11	0.17	0.40	1.66 Δ	0.32	0.4	1.36 Δ	0.16	0.4	1.68 Δ
12	0.19	0.40	1.62 Δ	0.34	0.4	1.32 Δ	0.09	0.5	1.82 Δ
13	0.17	0.40	1.66 Δ	0.32	0.5	1.36 Δ	0.11	0.4	1.78 Δ
14	0.21	0.40	1.58 Δ	0.32	0.5	1.36 Δ	0.2	0.4	1.60 Δ
15	0.22	0.40	1.56 Δ	0.34	0.4	1.32 Δ	0.07	0.5	1.86 Δ
16	0.24	0.40	1.52 Δ	0.36	0.4	1.28 Δ	0.22	0.4	1.56 Δ
17	0.22	0.40	1.56 Δ	0.22	0.5	1.56 Δ	0.22	0.4	1.56 Δ
18	0.21	0.40	1.58 Δ	0.28	0.5	1.44 Δ	0.17	0.4	1.66 Δ
19	0.25	0.40	1.50 Δ	0.4	0.4	1.20 Δ	0.18	0.4	1.64 Δ
20	0.23	0.40	1.54 Δ	0.31	0.4	1.38 Δ	0.11	0.5	1.78 Δ
21	0.25	0.40	1.50 Δ	0.25	0.5	1.50 Δ	0.19	0.4	1.62 Δ
22	0.21	0.40	1.58 Δ	0.21	0.5	1.58 Δ	0.23	0.4	1.54 Δ
23	0.24	0.40	1.52 Δ	0.32	0.4	1.36 Δ	0.17	0.5	1.66 Δ
Averages	**0.22**	**0.40**	**1.56 Δ**	**0.29**	**0.44**	**1.42 Δ**	**0.15**	**0.44**	**1.70 Δ**

Table 1. Training set images: L rate range
Optimum (ξ,δ) parameters and its corresponding DZS

	L			M		
	ξ	δ	DZS	ξ	δ	DZS
PSNR	0.22	0.40	1.56 Δ	0.26	0.40	1.47 Δ
MSSSIM	0.29	0.44	1.42 Δ	0.33	0.43	1.35 Δ
PSNRHVS	0.15	0.44	1.70 Δ	0.15	0.49	1.71 Δ
	H			VH		
	ξ	δ	DZS	ξ	δ	DZS
PSNR	0.28	0.40	1.44 Δ	0.34	0.40	1.31 Δ
MSSSIM	0.32	0.43	1.36 Δ	0.40	0.42	1.20 Δ
PSNRHVS	0.14	0.50	1.73 Δ	0.18	0.49	1.63 Δ

Table 2. Averaged (ξ,δ) parameters from the training set. Estimated optimums.

Now, we will proceed to evaluate the R/D performance of the UVDZQ with the images of the test set using the centroid of the optimum ξ and δ values (see Table 2) as estimated optimum values $\widehat{(\xi,\delta)}$ for the other images.

In Table 5 we show the average quality gains and rate savings of all images in the test set that may be achieved with this simple approach to estimate the optimum quantization parameter pair. As it can be shown, we obtain similar results of quality gain and rate savings than the ones obtained with the real optimum. In particular, we can obtain up to 11.08% of bit rate saving in the L rate range for PSNR and 512x512 image resolution and up to 7.71% of rate saving in the L bit rate range for PSNR-HVS and 2048x2560 image resolution.

Rate Ranges	PSNR			
	Quality gains (dBs)		% of Rate Savings	
	USQ	UDZQ	USQ	UDZQ
L	0.44	0.05	11.12	1.29
M	0.48	0.12	7.43	1.75
H	0.47	0.15	5.85	1.79
VH	0.34	0.28	2.80	2.21
	MSSSIM			
	Quality gains (Q units)		% of Rate Savings	
L	0.003	0.001	5.60	1.85
M	0.001	0.000	4.39	2.05
H	0.000	0.000	4.12	2.24
VH	0.000	0.000	2.68	2.47
	PSNR-HVS			
	Quality gains (dBs)		% of Rate Savings	
L	0.53	0.03	10.66	0.57
M	0.63	0.04	8.01	0.51
H	0.68	0.05	7.39	0.50
VH	0.58	0.08	4.28	0.53

Table 3. Averaged rate savings and quality gains for the training set, using the optimum parameters for each image

Rate Ranges	PSNR			
	Quality gains (dBs)		% of Rate Savings	
	USQ	UDZQ	USQ	UDZQ
L	0.50	0.07	15.18	1.86
M	0.58	0.17	10.50	2.55
H	0.66	0.22	11.17	2.70
VH	0.43	0.49	3.78	3.75
	MSSSIM			
	Quality gains (Q units)		% of Rate Savings	
L	0.005	0.003	11.23	3.92
M	0.003	0.002	7.77	3.57
H	0.001	0.002	10.09	3.82
VH	0.000	0.001	4.72	5.09
	PSNR-HVS			
	Quality gains (dBs)		% of Rate Savings	
L	0.59	0.06	15.29	1.33
M	0.82	0.10	13.03	1.35
H	1.12	0.10	16.35	1.00
VH	0.77	0.23	6.07	1.42

Table 4. Maximum rate savings and quality gains for the training set, using the optimum parameters for each image

5. Conclusions

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 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 different rate ranges under study covering an overall 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, using three different quality metrics, PSNR, MSSSIM and PSNR-HVS.

Rate Ranges	Image resolution 512x512				Image resolution 2048 x 2560			
	PSNR				PSNR			
	Quality gains (dBs)		% of Rate Savings		Quality gains (dBs)		% of Rate Savings	
	USQ	UDZQ	USQ	UDZQ	USQ	UDZQ	USQ	UDZQ
L	0.42	0.05	**11.08**	1.24	0.34	0.06	**7.44**	1.27
M	0.50	0.10	8.96	1.51	0.40	0.11	5.50	1.49
H	**0.53**	0.14	6.77	1.82	**0.44**	0.11	5.19	1.22
VH	0.34	0.30	2.71	2.43	0.35	0.21	2.72	1.69
	MSSSIM				MSSSIM			
	Quality gains (Q units)		% of Rate Savings		Quality gains (Q units)		% of Rate Savings	
L	**0.002**	0.001	4.93	1.16	**0.003**	0.001	**4.69**	1.80
M	0.001	0.000	**5.84**	1.43	0.001	0.001	3.07	3.26
H	0.000	0.000	4.77	2.05	0.001	0.000	3.10	3.35
VH	0.000	0.000	2.78	3.56	0.000	0.000	2.41	4.32
	PSNR-HVS				PSNR-HVS			
	Quality gains (dBs)		% of Rate Savings		Quality gains (dBs)		% of Rate Savings	
L	0.54	0.02	**10.88**	0.49	0.43	0.03	**7.71**	0.62
M	0.70	0.02	10.04	0.16	0.54	0.06	6.44	0.70
H	**0.78**	0.02	8.44	0.13	**0.64**	0.04	6.49	0.39
VH	0.58	0.06	4.18	0.48	0.60	0.07	4.27	0.53

Table 5. Test Set Average results, using estimated optimums.

From the results of the training set we obtain the estimated optimum quantizer parameters. This estimated optimums can be use to improve the R/D behavior of wavelet-base encoders. So, when comparing the R/D performance of a wavelet-based encoder with others, using one of the metrics in this study, a simple tuning of the quantizer parameters can provide better results. For that, the quantization stage in the wavelet encoder should be a UVDZQ tuned with the proposed parameter values. From the results we can see that the USDZQ quantizer schema is closer to the estimate optimum as its dead zone size is closer to the optimum, and so, if in the wavelet encoder is not possible to change the quantizer to a UVDZQ then is preferable to use a USDZQ than a USQ.

Resuming some of the results, we show that using the estimated optimum and for the two lowest rate ranges, bit rate savings up to a 11.08%, 5.84% and 10.88% can be obtained for 512x512 resolutions for the PSNR, MSSSIM and PSNR-HVS respectively. And for the 2048x2560 resolution images, up to 7.44%, 4.69% and 7.71% for the same rate ranges and metrics.

As future work 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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