Quantization Error Minimization by Reducing Median Difference at Quantization Interval Class

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***Abstract*—In this paper, a new technique to define the size of quantization interval is defined. In general, high quantization error will occur if large interval is used at a large difference value class whereas low quantization error will occur if a small interval is used at a large difference value class. However, the existence of too many class intervals will lead to a higher system complexity. Thus, this research is mainly about designing a quantization algorithm that can provide an efficient interval as possible to reduce the quantization error. The novelty of the proposed algorithm is to utilize the high occurrence of zero coefficient by re-allocating the non-zero coefficient in a group for quantization. From the experimental results provided, this new algorithm is able to produce a high compressed image without compromising with the image quality.**

***Index Terms*—Error Minimization; Quantization; Interval Class.**

I. Introduction

Quantization is one of the essential processes in compression task [1]. At the quantization step, the loss of information is introduced by deliberately rejecting the less important data in the image [2]. Quantization refers to a reduction of the precision of the point values of the wavelet transform, which are typically either 32 or 64 bit floating point numbers.

In designing the quantization algorithm, the size of interval gives a huge impact to the quantization performance. Generally, high quantization error will occur if large interval is used at high difference value bin. Thus, quantizer needs to be designed carefully to ensure the outfit of the interval size is efficient as possible to reduce the quantization error.

II. Related Work

Studies related to quantization algorithm for compression are found in scalar and vector domains for example, scalar quantization in [3]–[5] and vector quantization in [6], [7].

Uniform Quantization (see Figure 1) is the earliest and the simplest form of quantization algorithm. It considers all values as equally important and uniformly distributed. It works optimally in uniformly distributed signal. The interval is uniformly distributed and reconstruction level is also equally spaced.

Generally, the procedure is simple and fast, but some lost will be experienced due to the approximation of rounding process.

In contrast, non-uniform quantization (see Figure 2) has differences in boundary and interval. For non-uniform quantizer, the width of each group is different. The element is grouped based on a weightage fixed according to the needs.

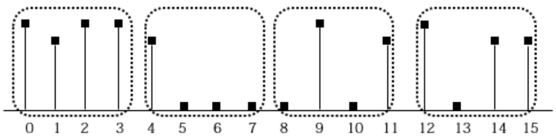

Figure 1: Uniform Quantizer

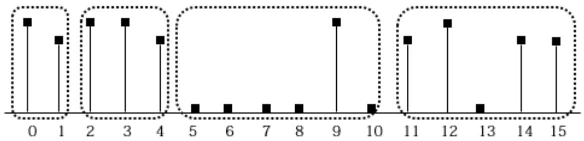

Figure 2: Non-Uniform Quantizer

In some recent work, for example [8] in his research proposed a dual mode quantization. He used a low and medium number of quantization level and fixed the code word length by using pixel value prediction in pre-processing stage. Linear prediction was performed, followed by both uniform and piecewise uniform quantization and differential encoding.

Meanwhile, Bartrina in her research proposed a cell based 2-step scalar deadzone quantization (2SDQ) scheme. This scheme can employ two steps quantization size depending on a small set of wavelet coefficient magnitude, called cell [9].

Although these two recent algorithms produce good image quality, they use the conventional uniform or non-uniform based quantization, which basically concern on reducing the cost of compression parameter, such as the length of the Code-word. Besides, the importance of location with respect to significant and non-significant coefficients is not considered in defining the quantization step as well as the quantization boundary.

III. Proposed Methodology

Our approach is different with the previous research in two main points: (1) the proposed algorithm takes zero coefficients, while optimizing the class interval size or step size (2) the group step size is defined by calculating the median error difference at each group and the interval size is recursively shifted until it reaches to a very minimum error value or no further exchange.

This strategy is done purposely to form a near optimal quantization process where significant coefficients are grouped into one quantization index. Then, the group interval size is iteratively shifted to form a very minimum median difference error value.

To visualize the process, let us consider an example with the 2^N element. N is 4, and the initial tone image, M is 4.

Consider the value, v of each coefficient, x is as in Figure 3:

v	10	8	10	10	8	0	0	0	0	10	0	8	10	0	8	8
x	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Figure 3: Coefficient value distribution

Each of the coefficients is mapped to an index Q[k_1,k_2], where [k_1,k_2] specifies its actual location. The coefficients with zero value are stored at its same location (see Figure 4), while the significant coefficients are grouped into another quantization index (see Figure 5).

As in this example, there are 10 significant coefficients, and they are retrieved from the previous 2^4 total number of coefficients, so the initial step size is 3.

$$s = round\left[\frac{10}{4}\right] \tag{1}$$

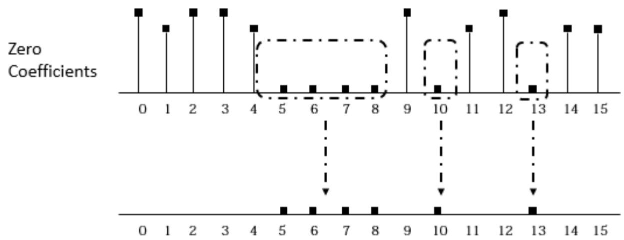

Figure 4: Mapping zero coefficient to an index Q[k_1,k_2]

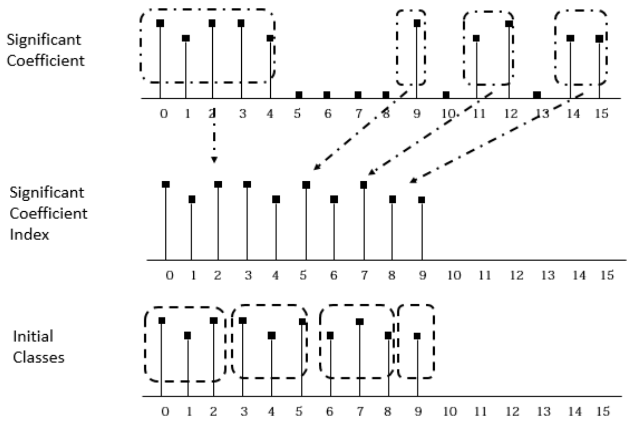

Figure 5: Construction of an initial classes for significant coefficients

Each iteration consists four groups, G. As for the first iteration, the member of G1 is {0,1,2}, G2 is {3,4,5}, G3 is {6,7,8} and G4 is {9}. The median value for G1 is 10, G2 is 10, G3 is 8 and G4 is 8. So, the total median different error for G1 is 2, G2 is 2, G3 is 2 and G4 is 0. Thus, the overall median different error for the first recursion is 6.

To seek a balance between the accuracy and the minimum error, each group interval is shifted, increased or decreased to perform the next new class set. It is done repeatedly until it reaches to n^{th} iteration, until no further median different error is decreased. At this point, the iteration is stopped.

Figure 6 illustrates the example of iteration process of the proposed algorithm.

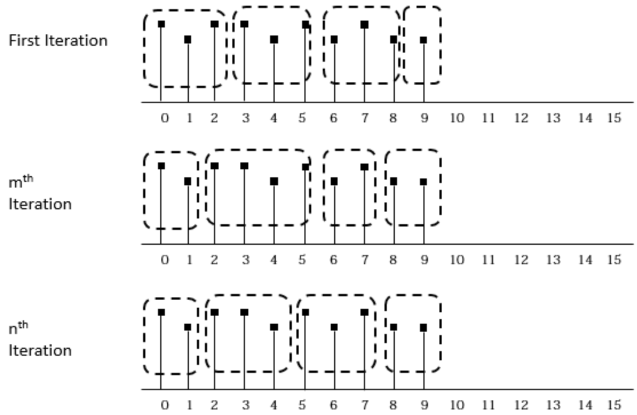

Figure 6: Example of iteration process of the proposed algorithm.

The remaining class set is subjected to default bit allocation procedure. 2 bits is used for each class since the class is 4.

00	01	10	11
G1	G2	G3	G4

Figure 7: Quantization Table Example

In this case, compression is archived by reducing 16 bin value that consumes 4 bits to only 4 bin value with only 2 bits used.

The block diagram of the proposed quantization algorithm is as shown in Figure 8:

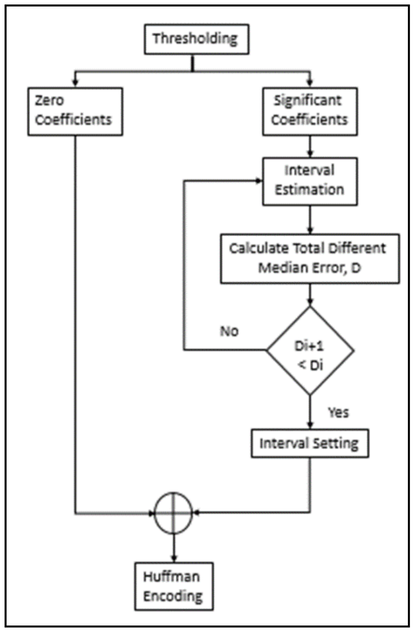

Figure 8: Proposed Quantization Algorithm

IV. RESULT AND ANALYSIS

A sequence test was conducted to demonstrate the performance of the proposed algorithm. First, the percentage error occurred during quantization process using Uniform, Non-Uniform and the proposed method was analyzed.

Based on the experiment, the percentage error of the proposed quantization algorithm showed the lowest error compared to Uniform and Non-Uniform quantizer. This is due to a greater image quality produced from the proposed algorithm. The step size or quantization interval in Uniform and Non-Uniform Quantization did not entertain the special characteristics of each image. Thus, it caused a low image quality and relinquished the boundary estimation.

As shown in Table 1, our proposed algorithm resulted in the minimization of the median error, hence the quantization error was significantly reduced.

Table 1
Quantization error percentage using various quantization algorithms

Image	Uniform Quantization	Non-Uniform Quantization	Proposed Quantization
Lena	50.48%	24.22%	23.01%
Mandrill	49.65%	24.06%	23.49%
Boat	49.38%	24.09%	23.49%
Woman	51.00%	28.02%	27.20%

Sequence of analysis were conducted to investigate the performance of the proposed compression algorithm. The performance evaluation used were the standard performance evaluation for image compression, which are the Peak Signal to Noise Ratio (PSNR) analysis and the Compression Ratio (CR) analysis [10]–[12].Then, the proposed algorithm were compared with the algorithm proposed by [8] and [9].

The objectives of the PSNR and the compression ratio analysis were to evaluate the quality of the reconstructed image and its final size after employing different quantization algorithm. Table 2 and Table 3 show the results of the PSNR and the compression ratio respectively.

Table 2
PSNR table of comparison between the proposed algorithm with recent researches

Images	M. S. Savic, [8]	J. Bartrina, [9]	Proposed
Lena	35.86	36.00	46.14
Mandrill	32.1483	35.98	44.36
Boat	31.9531	34.30	45.36
Woman	38.70	41.00	43.58

Table 3
Compression Ratio table of comparison between the proposed algorithm with recent researches

Images	M. S. Savic, [8]	J. Bartrina, [9]	Proposed
Lena	1.8	2.2	11.1
Mandrill	1.8	4.7	18.7
Boat	1.8	2.7	10.6
Woman	2.80	1.7	5.15

Note that the performance of the proposed algorithm shows a significantly better PSNR and compression ratio value compared to the existing one. Logically, this result expresses the efficiency of quantization process that quantizes the data by grouping the significant coefficient followed by an efficient minimization of the median quantization error. This procedure also takes the advantage of the existence of many zero coefficients on an image. At this point, zero coefficients are set aside at the first stage of quantization.

The main difference between our proposed compression algorithms with the existing one can be categorized in two areas.

First, the recent research does not consider the wavelet coefficient in relation to the importance of signal. Here, the calculated threshold is applied generally to the whole coefficient at the whole sub-bands without considering the complexity of the signal. Contrary to our proposed compression algorithm, the coefficient in each individual sub-band is entertained based on its characteristics. Thus, it enhances the threshold performance.

Besides, the proposed quantization algorithm gives an alternative strategy to the traditional uniform and non-uniform quantization concept used in the previous researches. By grouping the significant valued coefficient into a different group with zero valued coefficients, minimum median error difference was obtained.

V. Conclusion

In this research, we propose a new quantization method to enhance the ability in estimating the interval boundary for optimal quantization. Series of simulation and experiment process were conducted to evaluate and benchmark the proposed algorithm. The proposed algorithm successfully minimizes the error occurred during the quantization by recursively finding the optimum group interval size with the lowest possible error. Besides, our proposed method achieves more than 40dB for PSNR value, which is considered as very good because Human Visual System fails to distinguish any difference between the original and reconstructed image at this point and the compression ratio value of the proposed algorithm outperforms the existing one.

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