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# Efficient Quantization Method for Biometric Fingerprint Image Compression

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## Abstract

The choice of quantization method and the requirement to achieve a trade-off between compressed image quality and degradation are very crucial in the overall performance of a lossy image compression algorithm. In this paper, uniform and non-uniform scalar quantization schemes of biometric fingerprint image were studied. Comparative analyses of non-uniform quantization methods were also conducted and these include dither-based quantization and the Lloyd-Max quantization methods. The quality of the quantized output fingerprint image was determined in terms of Signal-to-Quantization Noise Ratio (SQNR). The degree of distortion or quantization error was determined in terms of the Mean Square Quantization Error (MSQE). The non-uniform quantization method performed better than the uniform quantization method in terms of the SQNR and MSQE values. It was also found out that, the performance of dither-based non-uniform quantization on biometric fingerprint image is not as efficient as the Lloyd-Max approach when the number of bits used in the quantization process increased. The results showed that the higher the number of bits used in the quantization process the higher the quality and the less the distortion in the resulting images.

*Keywords: Biometric fingerprint; image compression; quantization; dither.*

## 1 Introduction

Transform-based image compression is aimed at reducing image redundancy and identifying insignificant image pixels by isolating the various frequencies of the image. Image pixels frequencies are of paramount importance in the process of data coding because low frequency components which represent the approximation of the image correspond to the important or significant image features, whereas high frequency components which correspond to the details of the image (that is background and edges) are

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mostly represented by coefficients which are less important or insignificant [1]. Thus, when wavelet transform isolates the various frequencies of image pixels, coefficients that correspond to high frequencies can be quantized heavily while coefficients that correspond to low frequencies are quantized lightly or not at all after which the quantized output is entropy coded [1]. This is the principle behind lossy compression scheme.

The focus of this paper is on the quantization stage of an optimal compression system. Quantization is the process of mapping a large set of input values to a smaller set, such as rounding values to some unit of precision [2]. The round-off or truncation error introduced by quantization is referred to as quantization error or quantization distortion and it is the difference between the actual input source value and quantized output value. Quantization is crucial to digital signal processing systems and it forms the core of lossy compression algorithms [2,3]. Whenever image data are captured, they have to be quantized in order to store and transmit them digitally. The natural image with its infinite level of detail is mapped to a finite number, depending on the desired accuracy of the operation. In information technology and digital communications, there is relentless quest for developing efficient quantization techniques for compression that deliver optimal results depending on the particular input data. Therefore, the quantization algorithm has to recognize and retain the important features of the input data and then discard the unimportant ones without any waste of quantization levels [1].

In lossy image compression application, quantization is used in two ways, namely [1]:

i) If the data to be compressed is represented by large numbers, quantization is used to convert it to small numbers. This is because small numbers take less space than large numbers, thus compression is achieved by quantization;
ii) If the data to be compressed is analog, quantization is used to digitize it into a discrete set of small numbers. The smaller the numbers, the better the compression that is realized but also the greater the information loss.

It is therefore, of paramount importance to achieve a trade-off between the degree of data loss and compression ratio in the design of a lossy compression algorithm. In this research work, the source data for compression is a biometric fingerprint image. The fingerprint image is represented by a set of real numbers and these can either be uniformly quantized or non-uniformly quantized [1]. The quantized sequence where each symbol or pixel value appears in the source data with equal probability is uniformly quantized. However, when the symbols in the source data are not uniformly distributed, the sequence of quantized values should be realized such that the sequence are distributed in the same fashion as the original source image and are non-uniformly quantized [1].

## 2 Quantization

Source image data for lossy compression often must be quantized for cost-effective storage through efficient quantization method. The source input image such as the grayscale biometric fingerprint image under consideration in this research work is represented in 8-bits and this must be quantized using less number of bits than the original 8-bits. This process results in some form of distortion which is known as quantization noise. Fig. 1.0 shows a simple block diagram of the quantization process and the associated quantization noise.

In simple terms, a quantization process represents an input source of random variables with large symbols values with a quantized output with smaller symbol values. The quantized output is a close approximation of the source input signal. The output symbol values are predetermined values corresponding to the range of the input values and the number of bits allowed in the quantization process [4]. The design of a quantization system involves the specification of the decision intervals and corresponding output or representative levels and a mapping rule [4]. Since there are many possibilities to partition the input range, the focus of the research is on the efficient quantization method that minimizes a certain criterion or cost function such as degree of distortion in the process. There are two types of quantization and these include: scalar and vector quantization.

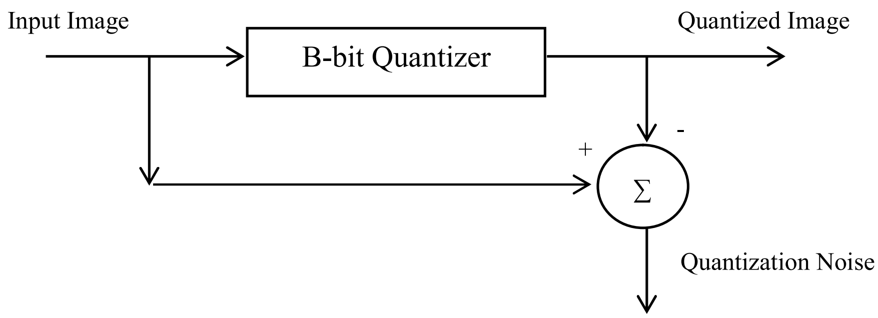


**Fig 1.0. Block diagram of quantization process and the associated noise**

## 2.1 Vector Quantization

In vector quantization, the source image is partitioned into equal-size blocks or vectors of pixels and the image encoder generates a list of blocks of the same size or lookup table, also known as codebook [1]. It should be noted that the process of generating and maintaining a codebook makes the vector quantization process a complex one [1]. Consequently, the implementation of a compression algorithm based on vector quantization is flawed by its high computational cost and complexity. Therefore, adopting a quantization method with less complexity such as scalar quantization that does not require codebook generation is advantageous in realizing a compression algorithm that is amenable to simple implementation.

## 2.2 Scalar Quantization

In scalar quantization, each input symbol of the source image is treated separately in producing the quantized output [5]. A quantizer can be specified by its input partitions or intervals and output levels (also called reconstruction values). If the input range is divided into levels of equal spacing, then the quantizer is termed as a uniform quantizer, and if not, it is termed as a non-uniform Quantizer [5].

## 2.3 Uniform Quantization

In a uniform quantizer, all source intervals or partitions are necessarily of the same size. A uniform quantizer has the following properties [3]:

i) The decision boundaries are spaced evenly;
ii) The reconstruction levels are also spaced evenly, with the spacing as the decision boundaries. The reconstruction levels are the midpoints of the intervals.

The constant spacing in a uniform quantizer's decision boundaries and reconstruction levels is referred to as the step size.

## 2.4 Lloyd Max non-uniform Quantization

Lloyd-Max quantization procedure defines an optimal approach to non-uniform quantization process. The basic idea of the Lloyd-Max quantization procedure is to find the decision boundaries and reconstruction levels that minimize the mean square quantization error (MSQE). This approach solves the problem of finding the decision boundaries $\{b_j\}$ and the reconstruction levels $\{y_j\}$ given N-level quantizer Q(x) on [a, b] so that the MSE given by Equation 1.0 can be minimized [3].

$$MSQE = \sum_{j=1}^{N} \int_{b_{j-1}}^{b_j} \left(x - y_j\right)^2 f_x(x)dx \tag{1.0}$$

Where:

$f_x(x)$ = The Probability Density Function (PDF) of the source input, X
$b_j$ = Decision boundary
$y_j$ = Reconstruction level
N = Quantization level
Setting the derivative of Equation 1.0 with respect to $y_j$ to zero, and solving for $y_j$:

$$y_j = \frac{\int_{b_{j-1}}^{b_j} x f_x(x)dx}{\int_{b_{j-1}}^{b_j} f_x(x)dx} \tag{2.0}$$

The reconstruction point for each quantization interval is the centroid of the probability distribution of the interval. Taking the derivative $y_j$ with respect to $b_j$ and setting it equal to zero, an expression for $b_j$ is obtained as follows:

$$b_j = \frac{y_{j+1} + y_j}{2} \tag{3.0}$$

In summary, the Lloyd-Max algorithm quantizes a source input by first partitioning its symbols into N initial sets or intervals. It then calculates the average point or centroid of each interval. It constructs a new partition by associating each symbol with the closest centroid. The centroids are then re-calculated to obtain new partition. The algorithm iterates these steps until convergence is reached, that is when centroids no longer change. It should be noted that when the source input distribution is uniform, Lloyd-Max quantization can also be used to quantize the source and in this case, the decision intervals are all equal [4].

## 2.5 Dither-based non-uniform quantization

When an image is quantized coarsely, a quantization noise or distortion occurs. One way to mitigate distortion is to modify the quantization process by adding a small amount of dither or random noise to the input image before quantization [4]. The dither can afterwards be subtracted from the quantized image. The dither perturbs the source input by a small amount such that pixels having more or less the same values in a neighborhood fall into different decision regions and are, therefore, assigned slightly different output levels. This is aimed at eliminating or minimizing the quantization noise [4]. Put differently, dither is an intentionally applied form of noise used to randomize quantization error with the objective of diffusing the error. This dither-based modification of non-uniform quantization process can be used to quantized image signals and its efficiency is dependent on the characteristics of the input source [4]. The dithering scheme can either be subtractive or non-subtractive.

## 2.6 Subtractive dithering quantization scheme

Suppose an independent signal v called a dither signal is added to an input signal x before quantization, this will give a combined signal w = x + v. Then the output of the quantization is Q(w). Thus, the quantization error $\epsilon$ of the system is given by [6]:

$$\epsilon = Q(x + v) - (x - v) \tag{4.0}$$

Where:

Q(w) = Quantization output
x = input signal
v = dither signal

If the independent signal v is subtracted from the quantization output, then the output becomes:

$$y = Q(w) - v \tag{5.0}$$

Thus, the total error $\epsilon$ of the dithered quantizer is given by [6]:

$$\epsilon = Q(w) - v - x \tag{6.0}$$

This procedure is shown schematically in Fig. 2.0, and is called subtractive dithered quantization.

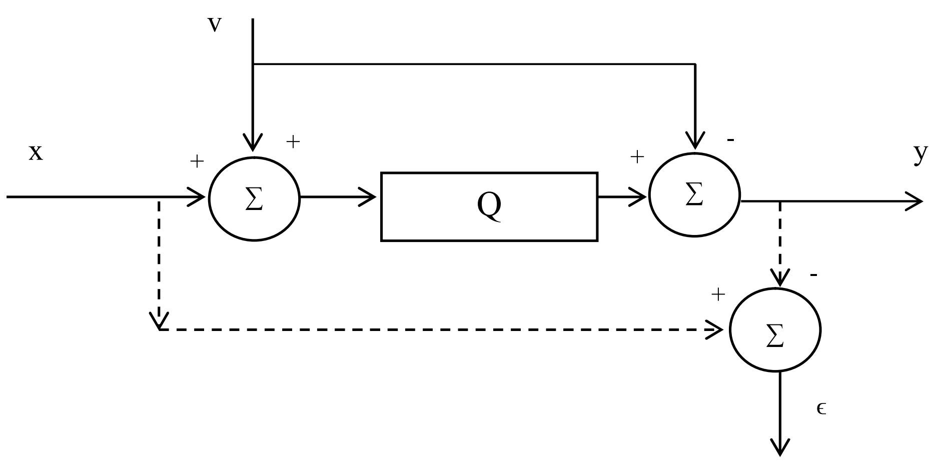


**Fig. 2.0. The Subtractive Dithered Quantization Schematic**

The most important limitation of subtractive dither is that it requires that the initially added dither signal be subtracted after quantization. In other words, it is required that all operations carried out on the dithered quantized signal before the dither is subtracted must also be performed on the dither signal. Consequently, subtractive dither is not a viable option in practice [6].

## 2.7 Non-subtractive Dithering Quantization Scheme

The problem with subtractive dither was that one needed to keep track of the dither signal that was used in order to subtract it later. Since this is not feasible for most practical applications, alternative method is needed. The first logical step is to study the properties of the quantization system if the dither signal is not subtracted after quantization. This is the essence of non-subtractive dither. A schematic of this procedure is shown in Fig. 3.0. The total error $\epsilon$ of the dithered quantizer is given by [6]:

$$\epsilon = Q(x + v) - x \tag{7.0}$$

The dither-modified non-uniform quantization method was employed for lossy compression in this research work for the purpose of comparative study with the Lloyd-Max non-uniform quantization to determine which is more efficient for the quantization of biometric fingerprint image.

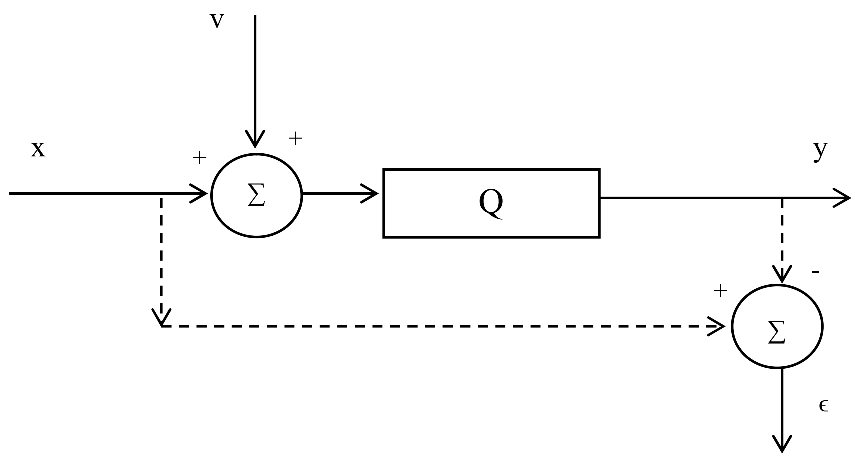


**Fig. 3.0. The Non-subtractive dithered quantization schematic**

## 2.8 Review of Lossy Compression Methods

The efficiency of the application of wavelet transform on image coding was significantly boosted by the introduction of embedded zero-tree wavelet (EZW) algorithm introduced by Shapiro [7]. The algorithm has since undergone significant improvements in the set partitioning in hierarchical trees (SPIHT) introduced by Said and Pearlman [8]. The EZW and SPIHT performed better than JPEG with most images. However, they both produced blurring effect on feature pattern of fingerprint images which renders the data useless for biometric application. Wavelet Scalar Quantization (WSQ) is a compression standard developed specifically for the compression of fingerprint images to improve the capability of preserving the fingerprint features for biometric pattern recognition. A compression ratio limit of 15:1 is specified for WSQ fingerprint compression standard [9]. In order words, its performance becomes unsatisfactory at compression ratio higher than 15:1 [10,11]. The embedded block coding with optimized truncation of embedded bit-streams (EBCOT) by Taubman [12] have resulted in modern wavelet image compression and coding techniques. As a matter of fact, the latest Joint Photographic Expert Group (JPEG 2000) image coding standard was developed based on the EBCOT algorithm [13,14]. The EBCOT-based JPEG2000 as a robust general-purpose compression standard has the limitation of not being able to adequately preserve the crucial biometric features of fingerprint images at high compression ratio and it has the problem of complex algorithm implementation. The JPEG was the earlier version of JPEG2000 standard and it was based on discrete cosine transform technique while the JPEG 2000 was based on wavelet transform technique [13-15].

The differences between JPEG2000 and WSQ standards are in their wavelet transform decomposition structures and the entropy coding method used. In wavelet decomposition, JPEG 2000 applies Mallat's algorithm or the pyramidal approach with Cohen Daubechies Feauveau (CDF), a variant Daubechies wavelet filter, while WSQ uses a fixed wavelet packet basis with the same CDF wavelet filter. WSQ uses raster scanning order, while JPEG2000 uses vertical bitplane scanning order [15]. More significantly, both standards are based on Daubechies wavelets and have been adopted as fingerprint compression standards. Arithmetic entropy coding method was used in JPEG2000 while Huffman coding was used in WSQ. However, for the quantization process, uniform scalar quantization was used in both compression standards [16]. It is noteworthy that JPEG 2000 is designed for general-purpose compression with significant flexibility. It has the disadvantage of complex algorithm implementation and high computation cost [16].

Based on the review of the existing lossy compression methods, vector quantization and uniform scalar quantization schemes were used. This accounted for the failure of the existing methods to preserve biometric fingerprint features at compression ratio higher than 15:1. Therefore, the development of a more efficient method of quantization is justified.

# 3 Aim and Objectives

The aim of this research is to carry out a non-uniform quantization of decorrelated source fingerprint image using Lloyd-Max quantization procedure to achieve efficient lossy compression. The objectives of the study are as follows:

i) Transformation of the source fingerprint image to lower the correlation of its pixel values and eliminate interpixel redundancy;
ii) Representation of large image pixel values with smaller quantized values to achieve efficient lossy compression of fingerprint image;
iii) Evaluation of the efficiency of the quantization process on the basis of Mean Square Quantization Error (MSQE) and Signal to Quantization Noise Ratio (SQNR) metrics to determine the extent of image quality and degradation in the lossy compression process;
iv) Comparison of the performance of uniform and non-uniform quantization methods, as well as, dither-based and Lloyd-Max non-uniform quantization schemes for biometric fingerprint compression.

# 4 Methodologies

The methodology adopted in this work is as follows:

i) Source fingerprint image transformation with Coiflet wavelet filters;
ii) Plot of histogram of source fingerprint pixel distribution;
iii) Non-uniform quantization of transformed source coefficients;
iv) Computation of the MSQE and SQNR values to compare the performance of uniform and non-uniform quantization methods as well as dither-based non-uniform quantization and Lloyd-Max non-uniform quantization schemes.

## 4.1 Source Fingerprint Image Transformation with Coiflet Wavelet Filters

Table 1.0 shows the source fingerprint data which were transformed using the Coiflet wavelet filters (See Appendix I for the appearance of source images). The process of transformation was used to lower the correlation between the image pixels and eliminate interpixel redundancy.

**Table 1.0. Source fingerprint images [9]**

| Filename | Size (byte) | Width (Pixel) | Height (Pixel) |
|---|---|---|---|
| Cmp00001.pgm | 356360 | 589 | 605 |
| Cmp00002.pgm | 638991 | 832 | 768 |
| Cmp00003.pgm | 638991 | 832 | 768 |
| Cmp00004.pgm | 612895 | 815 | 752 |
| Cmp00005.pgm | 638991 | 832 | 768 |
| Cmp00006.pgm | 638991 | 832 | 768 |
| Cmp00007.pgm | 347725 | 545 | 638 |
| Cmp00008.pgm | 600015 | 800 | 750 |
| Cmp00009.pgm | 347151 | 512 | 678 |
| Cmp00010.pgm | 197265 | 375 | 526 |

## 4.2 Histogram plot of source image

Each source fingerprint image is made up of an array (a matrix) of pixel values. The total number of pixel values in the array of transformed image coefficients were estimated and used to plot the histogram of the transformed image to determine the probability of occurrence of each image pixel or symbol. From the information generated from the histogram, the distribution of the input source symbols was determined based on the probability density function (PDF) of the image pixel distribution. Fig. 4.0 (b) shows the histogram plot of the 8-bit source fingerprint input and Fig. 4.0 (a) shows the histogram plot of 5-bit quantized fingerprint output at quantization level 32. The histogram plots were obtained using MATLAB image analysis tool.

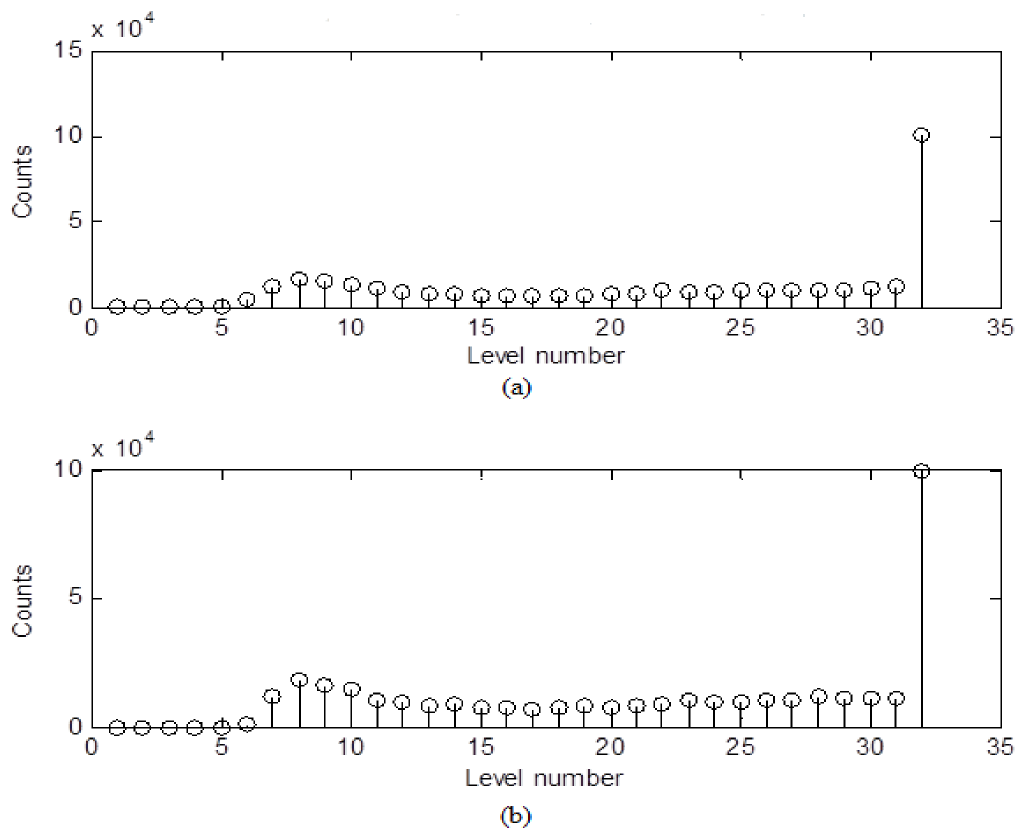


**Fig. 4.0. Histogram Plot of 5 bpp Quantized Fingerprint Output (a) and 8 bpp Source fingerprint Input (b)**

The histogram plots represent the pixel frequency distribution of the source fingerprint input and the quantized output. The two plots are nearly identical and the change is due to the difference between the 8-bits input image and the 5-bits quantized image. From the histogram plot the source fingerprint pixel distribution is not uniform and consequent upon this, uniform quantization method did not yield the best result. The analysis plot of the quantization levels against the decision regions or partitions for the uniform and non-uniform quantization process are as shown in Figs 5.0 and 6.0 respectively. It will be noticed from Fig 5.0 which represents the uniform quantization process that the process used equal quantization step sizes all through the source distribution to quantize the fingerprint image. Whereas in Fig. 6.0 the pixel values within the range of 0 to 50 are coarsely quantized with large step-size differently from the values in the range of 50 to 250 intensity values which are finely quantized with smaller step size for the non-uniform quantization process. This is significant because the non-uniform quantization method used large quantization step-size on the range of pixels with insignificant values and lower step-size to quantize the range of pixels with significant values. The method achieved compression by discarding the insignificant pixels and retaining the significant ones.

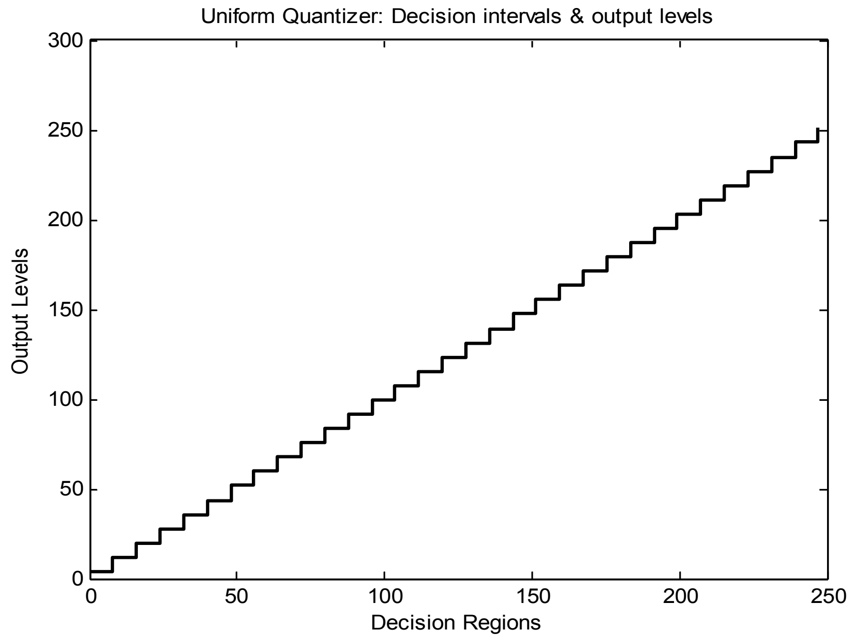


**Fig. 5.0. Plot of the Uniform Quantization Output Levels at 5 bpp**

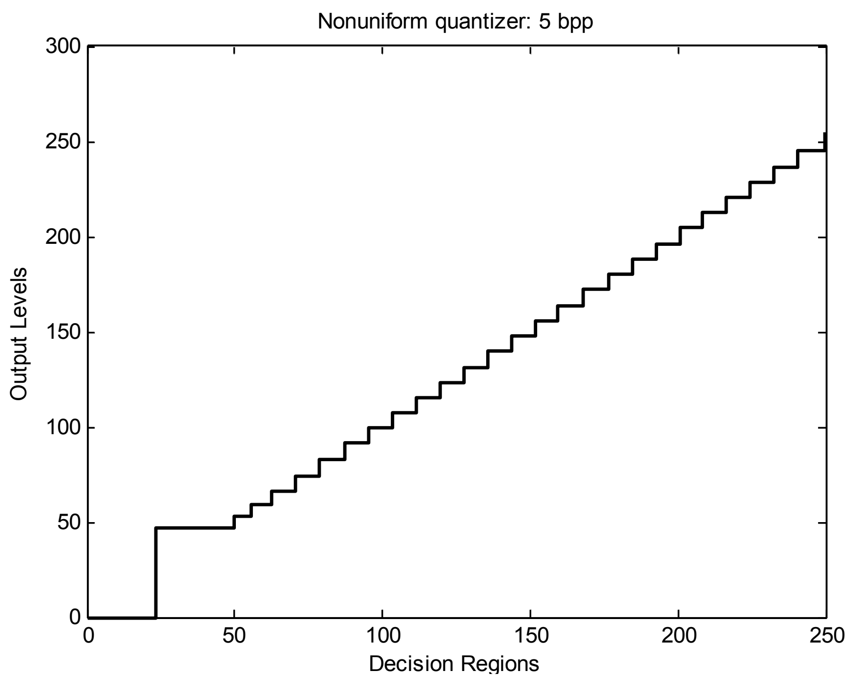


**Fig. 6.0. Plot of the Non-uniform Quantization Output Levels at 5 bpp**

## 4.3 Non-uniform quantization of transformed source fingerprint image

The source fingerprints acquired for this analysis [9] were 8-bit grayscale images and this means that 256 possible values of the image elements, that is 0 (black) to 255 (white). Lloyd-Max algorithm groups the pixel values of the source image into a number of partitions and measures the similarity between values in each partition. The algorithm starts by partitioning the source input set of values. It then calculates the average values, or centroid of each partition. It constructs a new partition by associating each value with the closest centroid. Then the centroids are recalculated for the new partitions and the algorithm repeats until convergence which is obtained when the centroids no longer change.

The Lloyd-Max quantization procedures involved the following steps:

i) Divide symbols (possible values) into M sets and the resulting partition is called initial set;
ii) The objective of Lloyd-Max algorithm is to minimize a distance metric within each set;
iii) Applied to the source fingerprint image, the algorithm minimizes the error between the corresponding value (reconstruction level) of an interval to its border (the thresholds);
iv) The thresholds are iteratively moved so that the partition changes iteratively, until there are no further changes or until convergence is reached.

The flowchart in Fig. 7.0 was developed and represents the various steps in the implementation of the Lloyd-Max quantization algorithm for lossy compression. The design parameters for the lossy compression algorithm areas shown in Table 2.0.

In Table 2.0, the quantization level, M was initialized based on the number of bits per pixel (bpp) used in the quantization process. The number of bpp used were 1 bpp to 7 bpp and this was because the original grayscale fingerprint images were represented using 8-bits. Therefore, in order to realize compression, the number of bpp lower than 8-bits should be used for quantization and this was done with the aim of achieving a tradeoff between image quality and the degree of degradation in the compression process. Since the quantization level $M = 2^b$, where b is the number of bits used per pixel for the quantization, therefore M is initialized to 2, 4, 8, 16, 32, 64 and 128 (for b = 1, 2, 3, 4, 5, 6, 7).

Based on the analysis flowchart in Fig. 7.0, MATLAB scripts were written to implement the various stages of the wavelet analysis of fingerprint image. The algorithm is detailed as follows:

1. Choose an initial set of M representative levels $x_{q,m}$. Pdf is then divided into M intervals;
2. Apply necessary centroid or threshold condition using Equation 8.0. This calculates (new) thresholds for each interval (centroid of $x_{q,m}$ and $x_{q,m+1}$);

$$t_{q,m} = \frac{x_{q,m+1} - x_{q,m}}{2} \tag{8.0}$$

3. Apply necessary minimum MSQE condition using Equation 9.0;

$$x_{q,m} = \frac{\sum_{i=u}^{v} x(i)p(i)}{\sum_{i=u}^{v} p(i)} \tag{9.0}$$

$x_{q,m}$ of each interval m=1, …, M is calculated to minimize MSQE.

The Mean Square Quantization Error of interval m, using pdf p (i) is given by:

$$MSE_m = \sum_{i=u}^{v} \left(x(i) - x_{q,m}\right)^2 p(i) \tag{10.0}$$

Where: i ranges over indices (u to v) in actual interval m;

$x(u) = t_{q,m}$ (lower threshold of interval m);
$x(v) = t_{q,m+1}$ (upper threshold of interval m);
$x(i)$ = current value in interval m;
$x_{q,m}$ = representative level of internal;
$p(i) = P(x(i))$: probability of symbol x(i).

4. The process is iterated. Step 3 and 4 are repeated until no further decrease in total MSQE;
5. Apply quantization on source image to output the quantized image.

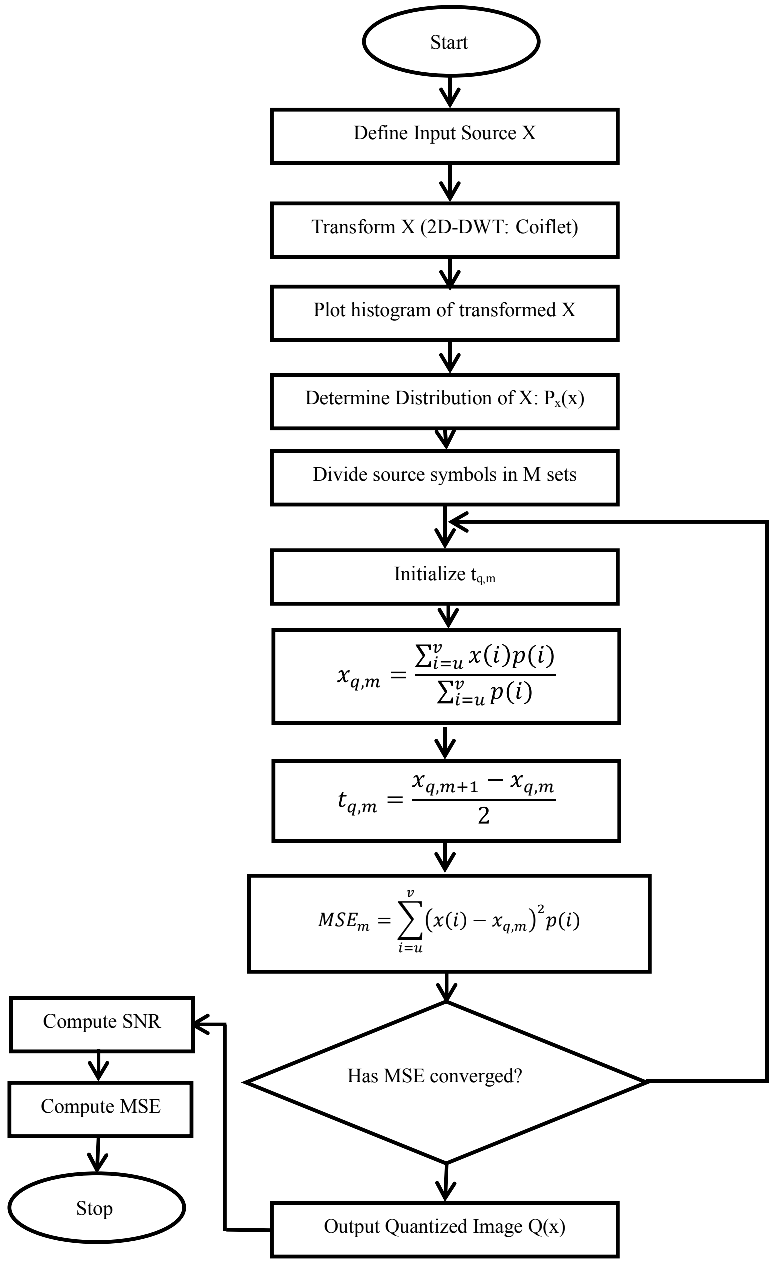


**Fig. 7.0. Flowchart of the Lloyd-Max quantization procedures**

**Table 2.0. Design parameters for Lossy compression based on Lloyd max algorithm**

| S/N | Design parameters | Values |
|---|---|---|
| 1. | Wavelet Transformation | Coiflets wavelets |
| 2. | Bits Per pixel (bpp) | 1 – 7 bits |
| 2. | Quantization Levels, M | $M = 2^b$ (where b = (bpp)) |
| 3. | Quality Metrics | SNR and MSQE |

After the iterative Lloyd-Max quantization procedure, the quality of the quantized output was estimated.

In addition, for dither-based non-uniform quantization process, random noise or dither signal was generated using the MATLAB function ‘rand’ and applied as a non-subtractive dither to modify the non-uniform quantization process in order to diffuse the quantization error. This is expected to further minimize the MSQE in the quantization process provided the biometric fingerprint image signal is suitable for this scheme.

# 5 Results and Discussions

The results of uniform and Lloyd-Max non-uniform quantization methods for source fingerprint images based on the MSQE and SQNR metrics are as shown in Table 3.0.

**Table 3.0. Comparison of the Non-uniform Quantization and Uniform Quantization Methods on the Basis of Quality and Distortion Measures**

| No. of Bits (Bits/Pixels) | Non-uniform quantization | | Uniform quantization | |
|---|---|---|---|---|
| | MSQE | SQNR (dB) | MSQE | SQNR (dB) |
| 1 | 8527.2 | -1.9204 | 1873.0 | 6.2924 |
| 2 | 667.9327 | 9.1403 | 551.6564 | 10.8670 |
| 3 | 64.416 | 19.2977 | 130.2040 | 17.0903 |
| 4 | 15.4413 | 25.5008 | 32.5056 | 22.9594 |
| 5 | 3.915 | 31.4603 | 8.2034 | 28.9540 |
| 6 | 0.9247 | 37.7277 | 2.1361 | 34.8221 |
| 7 | 0.1896 | 44.6083 | 0.6304 | 40.1349 |

These results represent the MSQE and SQNR values which are the measures of the image distortion and quality respectively. It was observed on the one hand that the SQNR values for non-uniform quantization increased from 19.2977 dB for 3 bpp to 44.6083 dB for 7 bpp whereas for the same range (3 bpp to 7 bpp) for uniform quantization, SQNR values increased from 17.0903 dB to 40.1349 dB. On the other hand, the MSQE values for non-uniform quantization decreased from 64.414 for 3 bpp to 0.1896 for 7 bpp while for the same range (3 bpp to 7 bpp) for uniform quantization, MSQE values decreased from 130.2040 for 3 bpp to 0.6304 for 7 bpp. It was also observed that the range of MSQE values for non-uniform quantization (64.416 – 0.1896) is much lower than that of uniform quantization (0.6304 - 130.2040) and higher range of SQNR values were recorded for non-uniform quantization as opposed to uniform quantization. These results indicated that the higher the number of bits used in the quantization process the higher the quality and the less the distortion in the resulting quantized images. Perhaps, more significantly, from 3 bpp and 7 bpp quantization, the results revealed that the non-uniform quantization consistently performed better than the uniform quantization method and this is depicted in the plots for SQNR and MSQE as shown in Figs. 8.0 and 9.0. The MSQE values plotted against the number of bits per pixel (bpp) in the uniform and non-uniform quantization processes is shown in Fig. 8.0 and it was revealed that MSQE values for non-uniform method was lower than that of the uniform method but as the number of quantization bits approaches 8-bits, the MSQE values for both methods are almost equal.

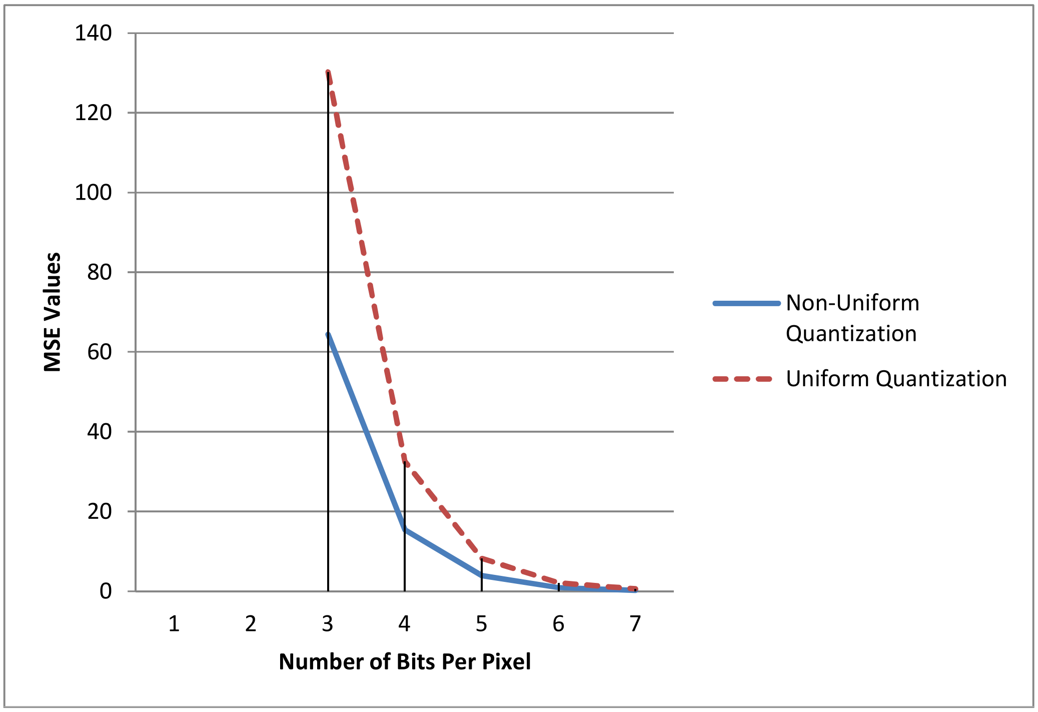


**Fig. 8.0. Plot of MSQE values for non-uniform and uniform quantization**

Fig. 9.0 shows the SQNR values plotted against the number of bits per pixel (bpp) in the uniform and non-uniform quantization processes and it was revealed that SQNR values for non-uniform method were higher than that of the uniform method.

In addition, the average MSQE and SQNR values at 5 bpp quantization for all the quantized fingerprint data showed that the performance of the non-uniform quantization is better than uniform quantization as the average MSQE and SQNR values for non-uniform quantizer are 3.4719 and 30.6351 dB respectively and that of uniform quantizer are 9.1580 and 27.8945 respectively. This is depicted in Table 4.0. Even though it was expected that these values will be the same for all source fingerprint image, it was observed that the variation in values was due to irregular quality of input source fingerprint data.

**Table 4.0. Average MSQE and SQNR Values for all Source Fingerprint Images at 5 bpp Quantization**

| Source input | Non-uniform Quantization | | Uniform Quantization | |
|---|---|---|---|---|
| | MSQE | SQNR (dB) | MSQE | SQNR (dB) |
| Cmp00001.pgm | 3.9150 | 31.4603 | 8.2034 | 28.9540 |
| Cmp00002.pgm | 2.9210 | 32.5243 | 10.2271 | 28.9122 |
| Cmp00003.pgm | 2.4440 | 27.1162 | 11.5165 | 23.8510 |
| Cmp00004.pgm | 2.7147 | 30.8053 | 10.6563 | 27.3187 |
| Cmp00005.pgm | 3.2589 | 31.8684 | 9.3364 | 28.8594 |
| Cmp00006.pgm | 3.0199 | 33.0683 | 9.8932 | 29.4617 |
| Cmp00007.pgm | 4.4182 | 30.5667 | 7.4407 | 28.8272 |
| Cmp00008.pgm | 3.0144 | 30.2710 | 10.1557 | 27.1857 |
| Cmp00009.pgm | 4.5747 | 28.7734 | 7.0335 | 27.4499 |
| Cmp00010.pgm | 4.4372 | 29.8972 | 7.1167 | 28.1250 |
| **Average** | **3.4718** | **30.6351** | **9.1580** | **27.8945** |

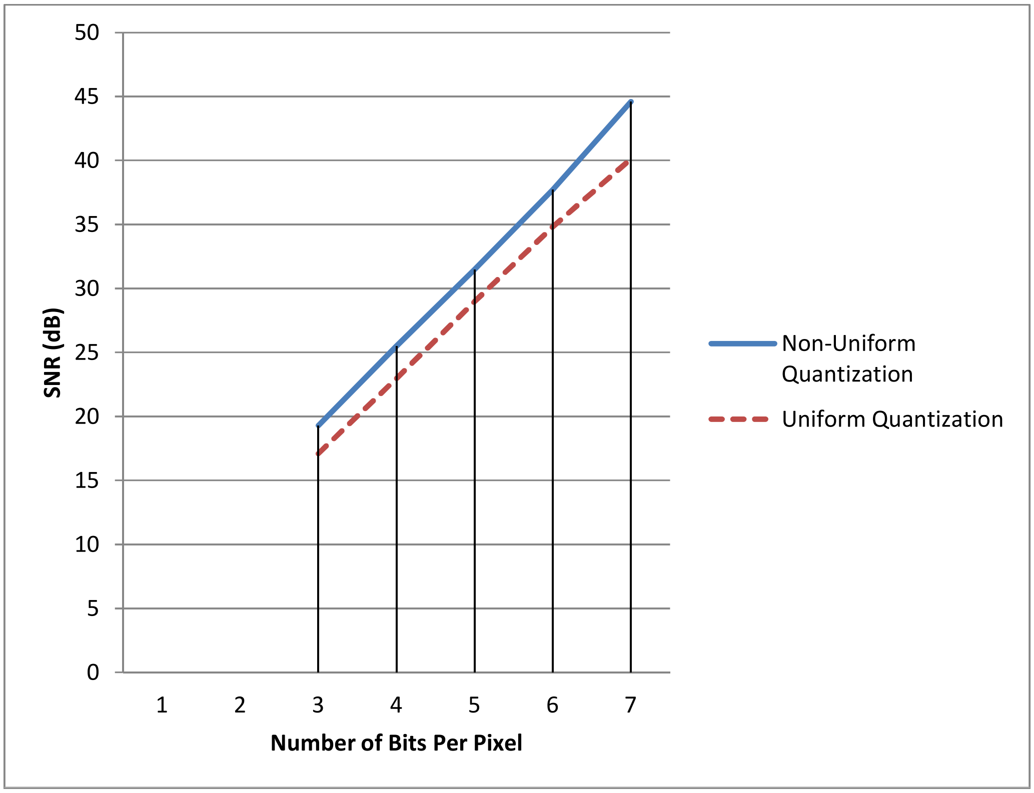


**Fig. 9.0. Plot of SQNR in decibels (dB) for non-uniform and uniform quantization**

The average SQNR value of 30.6351 dB is significant in that the quality of quantized images are satisfactory and this is because at SQNR value above 30.0 dB the degradation in the quantized images is visually imperceptible, that is the level of similarity between the original and quantized images is high. The SQNR values greater and equal to 30.0 dB are significant because at these values there is no visually perceptible difference between the original and the compressed images.

Furthermore, between 1 bpp and 2 bpp quantization, the performance of both quantization methods became unsatisfactory as the level of distortion which is a function of the MSQE value increased exponentially and the quality of the quantized image which is a function of the SQNR value decreased exponentially. The significance of this is that below 3 bpp quantization the performance of both quantization methods became unsatisfactory.

As shown in Table 5.0, the MSQE values obtained for dither-based non-uniform quantization scheme were higher than the ones obtained for Lloyd-Max scheme for the number of bits per pixel (bpp) from 2 to 7. However, for 1 bpp, the MSQE value obtained for dither-based quantization process was lower than that of Lloyd-Max method. Perhaps more significantly is the fact that the lower the bit number, the more the efficiency of the dither-based quantization process. On the other hand, the SQNR values for dither quantization scheme increased from 9.1082 dB to 35.0818 dB between 2 bpp and 7 bpp as opposed to higher SQNR values obtained for Lloyd Max scheme which increased from 9.1403 dB to 44.6083 dB for the same range of bit numbers. Whereas, for 1 bpp, the SQNR value obtained for dither scheme is -1.8637 dB and this value is higher than the value obtained for Lloyd-Max scheme which is -1.9204 dB. This means that the performance of dither-based non-uniform quantization on biometric fingerprint image is not as efficient as the Lloyd-Max approach for higher bpp values but as the bit number used in the quantization process decreases, the performance of dither-based scheme began to improve. These comparative inferences became evident from the plot of the MSQE values obtained for both scheme as shown in Figs. 10.0 and 11.0. In Fig. 10.0, it was observed that as the number of bits used in the quantization process decreases, the MSQE values obtained for dither-based quantization scheme got very close to the MSQE values for the Lloyd-Max quantization scheme. This means that the performance of both schemes became very close as the number of bits for quantization process was decreased.

**Table 5.0. Comparison of the Dither-Based Non-uniform Quantization and Lloyd-Max Non-uniform Quantization Methods on the Basis of Quality and Distortion Measures**

| No. of Bits (Bits/Pixels) | Dither-based non-uniform quantization | | Lloyd-max non-uniform quantization | |
|---|---|---|---|---|
| | MSQE | SQNR (dB) | MSQE | SQNR (dB) |
| 1 | 8416.7 | -1.8637 | 8527.2 | -1.9204 |
| 2 | 672.9086 | 9.1082 | 667.9327 | 9.1403 |
| 3 | 66.5738 | 19.1546 | 64.416 | 19.2977 |
| 4 | 17.0952 | 25.0590 | 15.4413 | 25.5008 |
| 5 | 5.4085 | 30.0569 | 3.915 | 31.4603 |
| 6 | 2.4012 | 33.5835 | 0.9247 | 37.7277 |
| 7 | 1.7006 | 35.0818 | 0.1896 | 44.6083 |

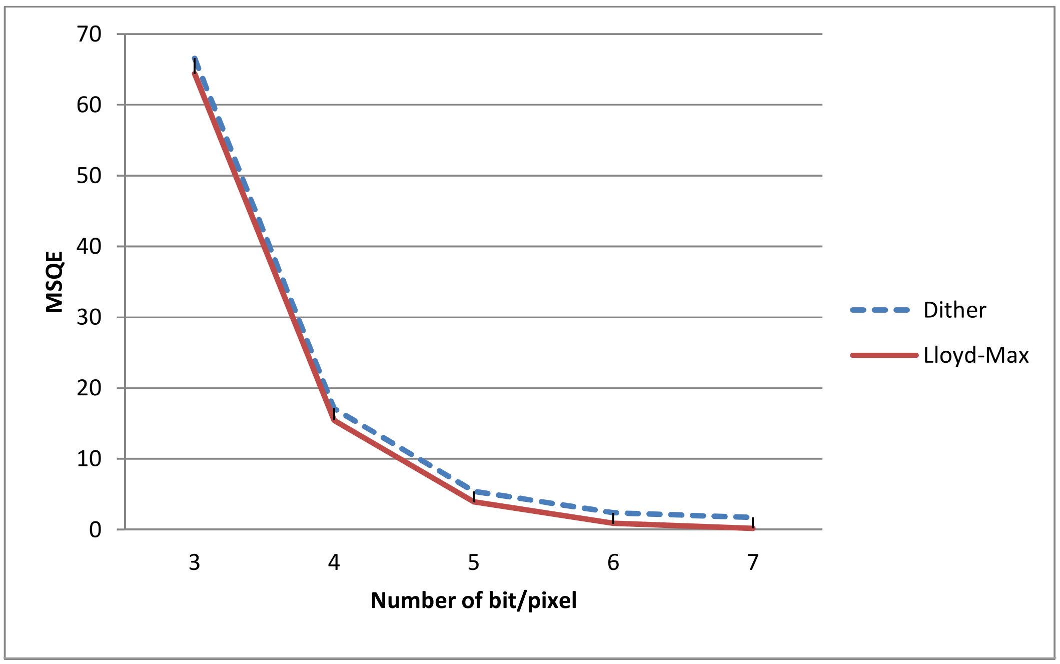


**Fig. 10.0. Plot of MSQE values for dither-based non-uniform quantization and Lloyd-Max non-uniform quantization schemes**

In the same vein, in Fig. 11.0, the gap between the SQNR values for dither-based quantization scheme and Lloyd-Max scheme gradually decreased as the number of bits was reduced from 7 bpp until the SQNR values became equal for both schemes at 3 bpp. Therefore, it stands to reason that discrete images with higher bit representation such as 16-bits and 24 bits are best suited for dither-modified quantization scheme because more number of bits will be available for manipulation in the process. However, Lloyd-Max non-uniform quantization is the preferred choice for 8-bit gray-scale biometric fingerprint image lossy compression based on the comparative analysis results.

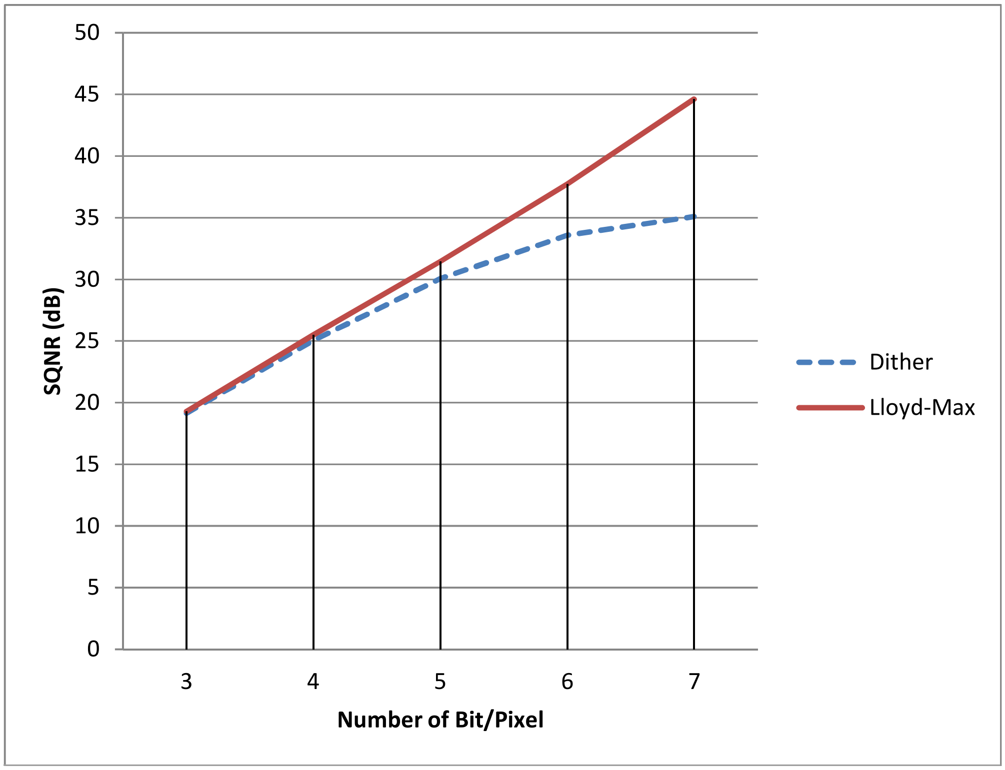


**Fig. 11.0. Plot of SQNR in decibels (dB) for dither-based non-uniform quantization and Lloyd-Max non-uniform quantization schemes**

# 6 Conclusions

In this paper, uniform and non-uniform scalar quantization schemes of transformed fingerprint image were studied. Comparative analyses of non-uniform quantization methods were also conducted and these include dither-based quantization and the Lloyd-Max quantization methods. The quality of the quantized output fingerprint image was determined in terms of Signal-to-Quantization Noise Ratio (SQNR). The degree of distortion or quantization error was determined in terms of the Mean Square Quantization Error (MSQE). The non-uniform quantization method performed better than the uniform quantization method in terms of the SQNR and MSQE values. The best result was obtained for number of bits per pixel (bpp) higher than 2 bpp. In addition, the SQNR values for dither quantization scheme were lower than the values obtained for Lloyd Max scheme between 2 bpp and 7 bpp. However, at 1 bpp, the SQNR value obtained for dither scheme was higher than the value obtained for Lloyd-Max scheme. This means that the performance of dither-based non-uniform quantization on biometric fingerprint image is not as efficient as the Lloyd-Max approach for higher bpp values but as the bit number used in the quantization process decreases, the performance of dither-based scheme began to improve. Therefore, even though dither-modified quantization scheme may be well suited for discrete images with higher bit representation such as 16-bits and 24 bits, Lloyd-Max non-uniform quantization is the preferred choice for 8-bit gray-scale biometric fingerprint image lossy compression based on the comparative analysis results.

# Competing Interests

Authors have declared that no competing interests exist.

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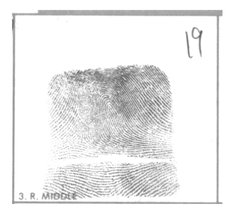
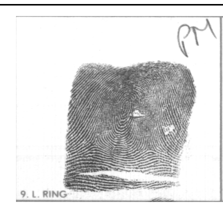
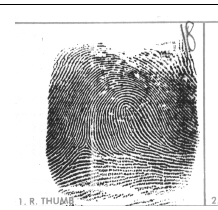
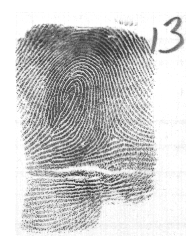
## APPENDIX I

**Source Fingerprint Images (obtained from NIST)**

| **Filename** | **Size (byte)** | **Source Fingerprint Images Display** |
|---|---|---|
| Cmp00001.pgm | 356360 |  |
| Cmp00002.pgm | 638991 |  |
| Cmp00003.pgm | 638991 |   |
| Cmp00004.pgm | 612895 |   |
| Cmp00005.pgm | 638991 |   |
| Cmp00006.pgm | 638991 |   |

| | | |
|---|---|---|
| Cmp00007.pgm | 347725 |  |
| Cmp00008.pgm | 600015 |  |
| Cmp00009.pgm | 347151 |  |
| Cmp00010.pgm | 197265 |  |



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