How Many Gray Levels are Required to Represent a Gray Texture Image Using Histogram Equalization?

Manuel Alberto Medina Jr. and Chaur-Chin Chen

Institute of Information Systems and Applications, National Tsing Hua Univeristy, Taiwan

ABSTRACT

Most gray images don't always require an 8-bit representation for each pixel; in particular, a pixel of texture images may even be coded in no more than 5 bits (32 gray levels). Adequately enough it is probable that between 16 to 32 levels of gray could be a suitable threshold for most gray level texture image representation, before the image shows signs of false contouring or any notable rough edges. This research uses a variety of texture images that have been re-quantized according to histogram equalization: a methodology that increases the contrast of an image by using the image's histogram. All the data gathered were from a survey conducted by 50 independent test subjects. A nonparametric sign test indicates that 8 levels would be enough to encode a gray texture image for most of the test images from Brodatz' album.

Keywords: Histogram Equalization, PSNR, Sign Test, Texture Images.

1. Introduction

The field of digital image processing refers to the processing of digital image by means of a digital computer. Hence, two of the major driving forces of interest in digital image processing methods are: improving image data for human interpretation, and processing image data for storage, transmission and representation for machine vision (Gonzalez and Woods, 2002). Digital images exist everywhere, each of which can be defined as a function $f(x, y)$ in $\{0,1, \ldots,255\}$ – with x and y being spatial coordinates.

Digital images are composed of finite number of elements (pixels), and in many machine vision and image processing methods, assumptions are made about the uniformity of intensities (of these pixels) in local image regions (Chen and Pau, 1999). Many real world images do not exhibit regions of uniform intensities. For example, the image of a wooden surface (texture) is not uniform but contains variations of intensities which form certain repeated patterns called *visual primitives*. The patterns are a result of physical surface properties such as roughness or oriented strands which often have a tactile quality, or they could be the result of reflectance differences such as the color on a surface or light.

Texture is a ubiquitous visual experience and a very important characteristic of a digital image. It has been used in various applications, such as carpet quality control, region recognition in satellite images, and body painting control in the vehicle industry (Chen and Chen, 1999; Chen and Chen, 2003). Moreover, one defining factor of texture images is that it exhibits a spatial distribution of gray values (gray levels). The term gray level generally describes the monochromatic intensity of an image because it ranges from black to gray and finally white. Depending on the acquisition method of a texture image, an image may exhibit various levels of contrast and require modification for better interpretation. For example, in medical x-ray images of bones, images are sometimes required to be intensified for better clarification. Such modifications can be applied to an image by the use of histogram equalization.

The remainder of this work is organized as follows. Section 2 reviews histogram equalization, Section 3 presents the method and experiment conducted for this work. Section 4 describes the analysis and results of the experiment, and lastly Section 5 summarizes the overall work with a given conclusion.

2. Histogram Equalization

The goal of histogram equalization is to obtain a uniform histogram for the output image; this transformation is achieved by employing a monotonic, non-linear mapping which re-assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities (Histogram, 2009). In other words, this allows for areas of lower local contrast to gain a higher contrast without affecting the global contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values, thus the intensities can be better distributed on the histogram (Histogram, 2009). In addition, because of its effectiveness in detail enhancement this technique is used in image compression processes and in the correction of non-linear effects introduced by digitizers or various display systems.

2.1. *Histogram Equalization Process*

Histogram equalization is usually introduced using continuous, rather than discrete, process functions. As a result, we will consider for a brief moment continuous functions, where r represents the gray levels of the image to be enhanced (Gonzalez and Woods, 2002). Therefore, we assume that the images contain continuous intensity levels (in the interval $[0,1]$) with $r = 0$ representing black and $r = 1$ representing white (Histogram, 2009). Subsequently, we will look at a discrete formulation which will allow pixel values to be within the interval $[0, L-1]$.

We now look at the transformation function of the form

$$s = T(r) \qquad 0 \le r \le 1, \qquad (2.1)$$

for any r within the aforementioned interval this formula produces a level s for each pixel r in the original image. Figure 1 shows an example of the pixel distribution using a x^2-distribution. To be successfully implemented we will assume that the transformation function $T(r)$ satisfies the following two conditions.

1.) $T(r)$ is single-valued and monotonically increasing within the interval $0 \le r \le 1$; and
2.) $0 \le T(r) \le 1 \; for \; 0 \le r \le 1$.

The first condition needs to be single-valued since we need to ensure that the inverse transformation exists. The reason for its monotonicity condition is to control the increasing order from black to white in the output image. The latter condition is to guarantee that the output gray levels will be in the same range as the input gray levels (Gonzalez and Woods, 2002). If the transformation function was not monotonically increasing then we would have only a section of the intensity range being inverted. Therefore, we can denote the inverse transformation function from s back to r as

$$r = T^{-1}(s) \quad 0 \leq s \leq 1. \qquad (2.2).$$

Gray levels in an image can be viewed as random variables within [0, 1], to describe these random variables we use their probability density functions (P.D.F). Let, $p(r)$ and $p(s)$ denote the P.D.F of random variables r and s respectively. If $p(r)$ and $T(r)$ are known and $T^{-1}(s)$ satisfies condition (1), then the P.D.F function $p(s)$ of the transformed variable s can be obtained by

$$p(s) = p(r)\left|\frac{\mathrm{dr}}{\mathrm{ds}}\right|. \qquad (2.3)$$

This function shows that the probability density function of the transformed variable, s, is determined by the gray level P.D.F of the input image and also by the chosen transformation function (Gonzalez and Woods, 2009). Therefore, the transformation function, $s = T(r)$ for histogram equalization is:

$$s = T(r) = \int_0^r p(u)du \qquad (2.4)$$

which is called the cumulative distribution function (C.D.F) of random variable r.

Figure 1 shows a x^2distribution with degrees of freedom 4 using the aforementioned C.D.F. along with the P.D.F function below.

$$f(x) = \frac{1}{4}xe^{-\frac{x}{2}} \qquad ,x \geq 0 \qquad (2.5)$$

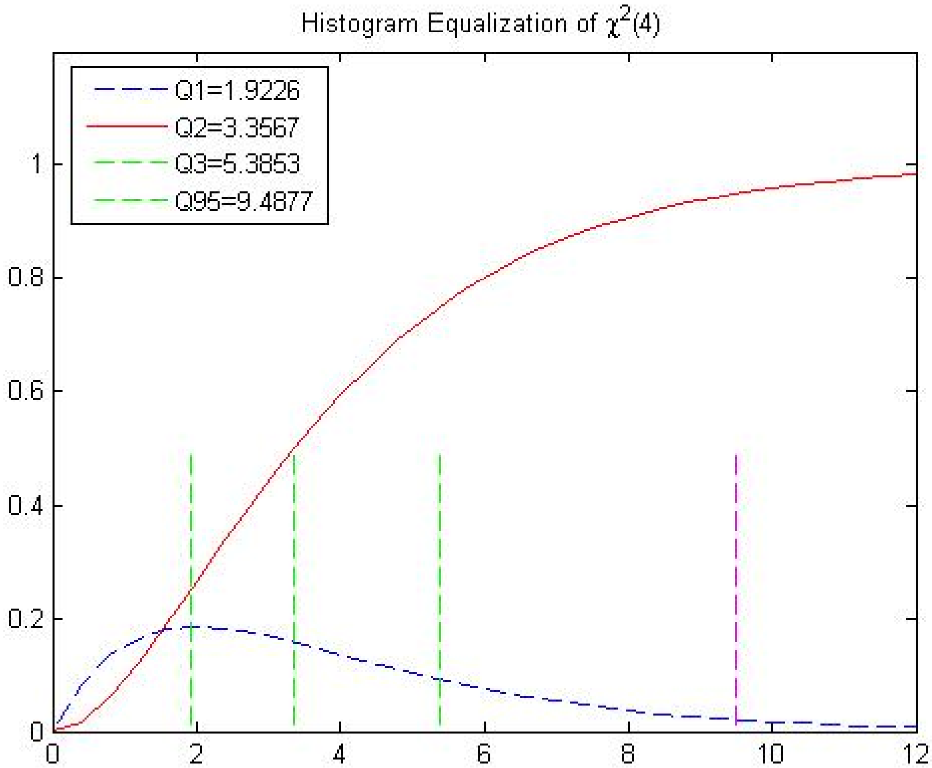


Figure 1: x^2-Distribution with degrees of freedom 4.

For a discrete gray image, a pixel r_i takes one of L discrete values. The probability of occurrence of gray level r_i in an image is approximated by

$$p(r_i) = \left|\frac{n_i}{n}\right| \qquad i = 0,1,2,\dots,L-1. \qquad (2.6)$$

where n is the total number of pixels in the image, n_i is the number of pixels that have gray level r_i and L is the total possible gray levels in the image. Furthermore,

$$s_i = T(r_i) = \sum_{j=0}^{i} p(r_j) = \sum_{j=0}^{i} \frac{n_j}{n} \qquad i = 0,1,2,\dots,L-1. \qquad (2.7)$$

Hence, the output image is obtained by mapping each pixel with level r_i in the input image into a matching pixel with level s_i in the output image using the equation above.

3. Methodology

The goal of our research is to be able to find and calculate the minimum adequate number of levels we require to represent an image. To achieve this, we devised a simple experiment to collect the necessary data; the methodology includes a basic survey (data acquisition) and statistical analysis (of acquired data) to calculate the actual number of gray levels. In this section we will look at how that experiment was set up for data acquisition.

3.1. *Data Acquisition Process*

First and foremost, before we actually started conducting the survey to collect the necessary data we had to decide which images and levels of gray we would actually use for this experiment. As we know texture is one of the important characteristics of a digital image thus deciding which images to use is important, since not all the images were of high quality (i.e. contrast difference). This experiment used images that have been digitally scanned from (Brodatz, 1966), a total of 80 images were used. All the images were gray intensity images with 512 x 512 in dimension as shown in Figure 2 below.

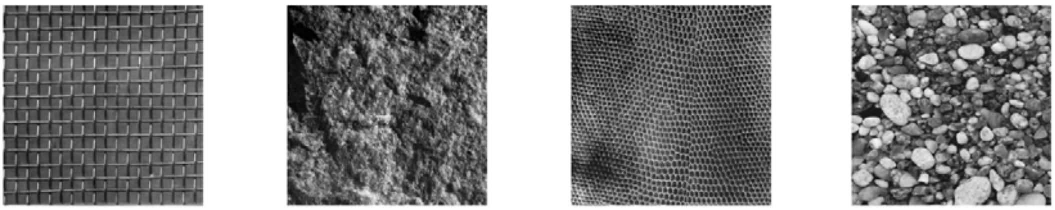
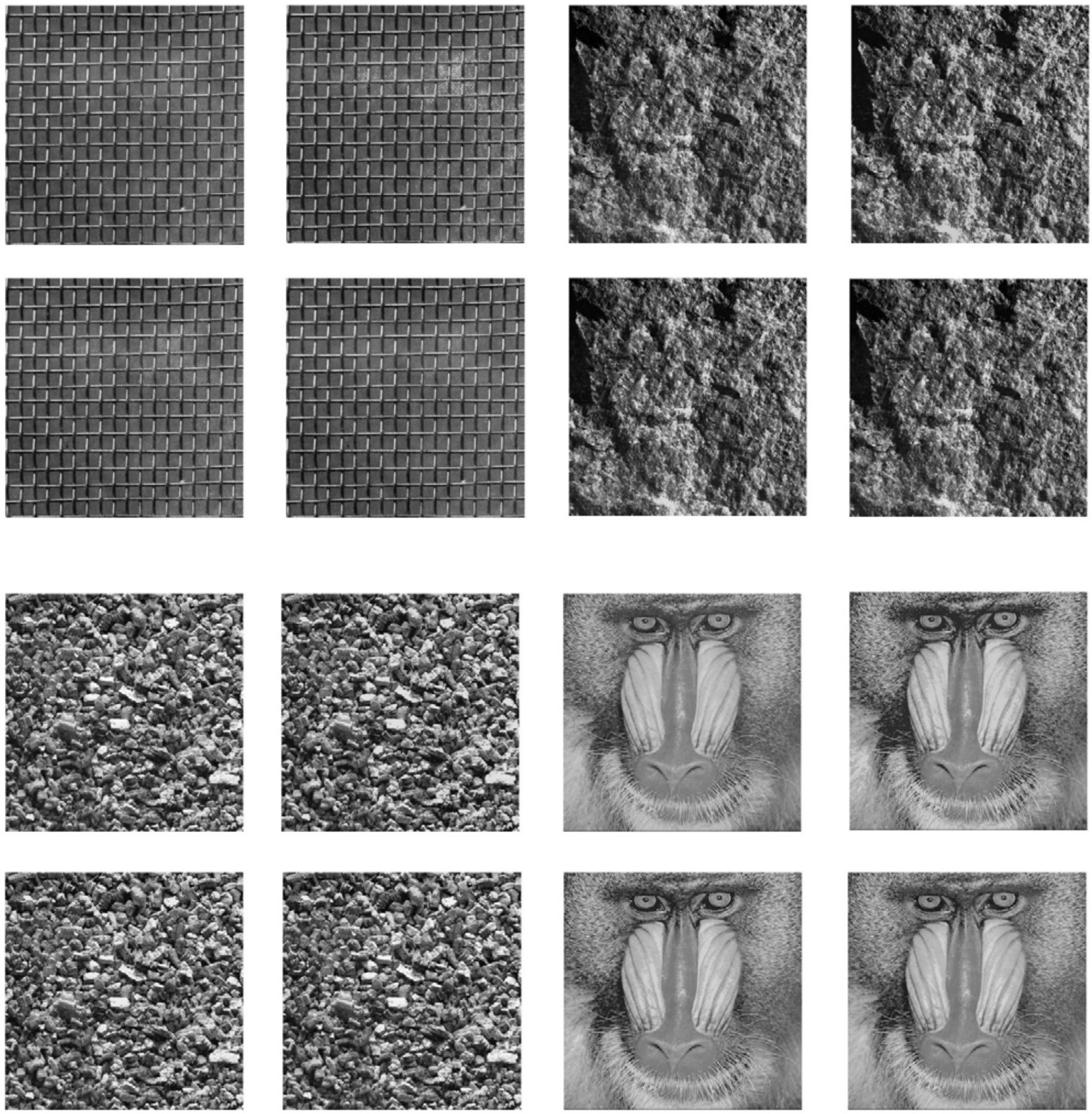


Figure 2: Images from Brodatz (Brodatz, 1966)

We well know that images don’t necessarily require an 8-bit representation; sufficiently enough they can be coded in 5 bits (32 gray levels) representation; hence, the reason for this experimental survey. Each of the original images (80 images) as shown in Figure 2 above, is originally coded in an 8-bit representation (256 gray levels). This experiment looks at 3 other distinct bit representations of these images, in other words, each of the 80 images where re-coded in 3-bit (8 levels), 4-bit (16 levels) and 5-bit (32 levels) representation. This result was achieved using the aforementioned histogram equalization method in Chapter 2. Thus each image was parsed by the equalization program and converted to its respective bit representation (3, 4, 5 bits); the end result was displayed using 4 different bit representations as shown in Figure 3 below.



a	b
c	d

Figure 3: Image Samples of D01, D02, D05, Mandrill, Lenna, and D25 with varied bit representations (a) Original image 8 bit, (b) 3 bit (c) 4 bit and (d) 5 bit

As seen in the Figure 3 above, we can easily have a clear overview of all images; however, one cannot instantaneously note the difference among each image. Keep in mind that 3 of the images have been altered using the histogram equalization process. In order to successfully execute this experimental survey, each test subject (student) was shown all 80 images in a slide show. However, each test subject was only given 5-6 seconds to view each set of images, their main purpose in this survey was to see if they could distinguish any real significant difference among the 3 images from the original. A simple answer sheet was provided to each subject to write down their corresponding answer. Basically, the answers included Y (Yes) if any significant difference was noted, N (No) if no difference was noted, and X for not being able to distinguish any difference or being uncertain. Figure 4 below shows the answer sheet used in this survey; note the square figures in the answer sheet are a reflection of how the images were set up in the slide show. Notice that each square figure is properly labeled in accordance to how the images appeared in the slide show. Also, each of the square figures on the answer sheet has an **O**; this shows the test subjects that, that particular image is in fact the original images that they must use as comparison to the other 3 images. Finally, the sample size for this experimental survey was a total of 50 test subjects. After all the data had been collected it was analyzed and tabulated in a spread sheet, each of the answers (i.e. Y or N) were tabulated as 1 or 0 respectively and -1 for X (uncertain answer); a sample is shown in Figure 5.

ID: ____________________________ **ANSWER SHEET**

Image 1: D01.raw

O	

Image 2: D02.raw

O	

Image 3: D03.raw

O	

Image 4: D04.raw

O	

Image 5: D05.raw

O	

Image 6: D06.raw

O	

Image 7: D07.raw

O	

Image 8: D08.raw

O	

Image 9: D09.raw

O	

Image 10: D10.raw

O	

Image 11: D11.raw

O	

Image 12: D12.raw

O	

Image 13: D13.raw

O	

Image 14: D14.raw

O	

Image 15: D15.raw

O	

Image 16: D16.raw

O	

Image 17: D17.raw

O	

Image 18: D18.raw

O	

Image 19: D19.raw

O	

Image 20: D20.raw

O	

Image 21: D21.raw

O	

Image 22: D22.raw

O	

Image 23: D23.raw

O	

Image 24: D24.raw

O	

Figure 4: Answer Sheet Sample

TEST SUBJECT	IMAGE ID	3 Bit (L=8)	4 Bit (L=16)	5 Bit (L=32)
1	D01: Woven aluminum wire	0	1	-1
1	D02:Fieldstone	0	1	1
1	D03:Reptile skin	1	1	-1
1	D04:Pressed Cork	0	1	1
1	D05:Expanded mica	1	0	1
1	D06:Woven aluminum wire	0	1	1
1	D07:Fieldstone	0	1	1
1	D08:Absolute illusion of woven wire	0	0	1
1	D09:Grass lawn	0	0	1
1	D10:Crocodile skin	1	0	0
1	D11:Homespun woolen cloth	0	1	0
1	D12:Bark of tree	0	0	1
1	D13:Bark of tree	0	1	1
1	D14:Woven aluminum wire	0	0	1
1	D15:Straw	0	0	1
1	D16:Herringborn weave	0	1	1
1	D17:Herringborn weave	0	1	0
1	D18:Raffia weave	0	1	1
1	D19:Woolen cloth	1	1	0
1	D20:French canvas	1	0	0
1	D21:French canvas	0	1	-1
1	D22:Reptile skin	1	0	1
1	D23:Beach pebbles	0	0	1
1	D24:Calf Leather	0	0	1
1	D89:Dry hop flowers	0	0	1
1	D26:Ceramic-coated brick wall	0	1	1
1	D27:Beach sand and pebbles - translucent effect	0	0	1
1	D28:Beach sand	0	1	1
1	D29:Beach sand	0	0	1
1	D30: Beach pebbles - translucent effect	0	1	0
1	D31:Beach pebbles with hard, dry appearance	0	1	0
1	D79:Oriental grass fiber cloth	0	0	1
1	D88:Dry hop flowers	0	1	1
1	D90:Clouds	0	1	1
1	D35:Lizard skin	1	0	0
1	D36:Lizard skin	0	0	1
1	D37: Water	0	1	0
1	D38:Water	0	0	1
1	D39:Lace	0	1	1

1	D40:Lace	1	1	1
1	D41:Lace	0	1	1
1	D42:Lace	0	1	1
1	D43:Varied swinging of light bulb on a length of wire	0	1	1
1	D44:Swinging lights in a darkened room	0	1	1
1	D45:Abstract effect of swinging light	0	1	1
1	D46:Woven brass mesh	0	1	0
1	D47:Woven brass mesh	0	1	0
1	D48:Perforated masonite panel	1	1	0
1	D49:Straw screening	0	0	1
1	D50:Raffia woven with cotton threads	0	0	1
1	D51:Raffia woven with cotton threads	1	0	1
1	D52:Oriental straw cloth	0	1	1
1	D53:Oriental straw cloth	0	1	0
1	D54:Beach pebbles	0	1	0
1	D55:Straw matting	0	0	1
1	D56:Straw matting	1	0	1
1	D57:Handmade paper	0	0	1
1	D58:European marble	0	0	0
1	D59: European marble	1	0	1
1	D60:European marble	1	1	1
1	D61:European marble	0	1	1
1	D62:European marble	0	1	1
1	D63:European marble	0	1	1
1	D64:Handwoven Oriental rattan	1	1	0
1	D65:Handwoven Oriental rattan	0	1	1
1	D66:Plastic pellets	0	0	1
1	D67:Plastic pellets	0	1	1
1	D68:Wood grain	0	0	1
1	D69:Wood grain	0	1	0
1	D70:Wood grain	0	1	1
1	D71:Wood grain	0	1	1
1	D72:Tree stump, used as a chopping block	1	1	1
1	D73:Soap bubbles	0	1	0
1	D74:Coffee beans	0	1	1
1	D75:Coffee beans	0	1	1
1	D76:Oriental grass fiber cloth	1	0	1
1	Lenna	1	1	1
1	Fingerprint	0	1	1
1	Koala	0	1	1
1	Mandrill	1	0	1

Figure 5: Images used in survey

4. Result and Analysis

In this chapter we will analyze and describe the results obtained from the statistical analysis. Note Figure 5 above shows the different images used as well as their respective data. All the data was used to calculate the index of each image, which determined the adequate bit coding that is required to represent a gray scale image. However, in order to facilitate the calculation of the statistical index, the data was filtered and grouped according to image name (i.e. D01), by doing so it was easier to read and calculate the index for each specific image. The remainder of the chapter discusses the method used for the index calculation (sign test) and explains the end result of said experiment.

4.1 *The Sign Test*

Many statistical tests require that your data follow a normal distribution, however, in some cases this is not so. Sometimes it may be possible to transform your data to follow a normal distribution, in other instances it may not, because the sample size may be too small to actually ascertain whether or not the data is normally distributed. In the latter case it is necessary to use a statistical test which does not require the data to be normally distributed. Such a test is called a nonparametric or distribution free test.

Nonparametric statistics is a body of inference procedures that is valid under a much wider range of shapes for the population distribution. The term *nonparametric inference* is derived from the fact that the usefulness of these procedures does not require modeling a population in terms of a specific parametric form of density curves, such as normal distributions (Bhattacharyya and Johnson, 1977). There exists a variation of nonparametric test; one such test is called the sign test. This nonparametric test is notable for its intuitive appeal and ease of application. As its name suggests, this test utilizes only the signs of the differences of the N pairs. In this experiment the sign test is used to test the null hypothesis H, which states that *no significant difference exists between a re-quantized image and the original*. As previously mentioned, during the experimental survey the data gathered from the test subjects (Y and N) were converted to binary "1" and “0” respectively. The test statistic is the sum of these values, and the question of interest is the frequency with which a random assignment of "1" and "0" within each pair yields as extreme a value (whether high or low) as the observed data.

For large samples, the sign test can be performed by using the normal approximation to the binomial distribution (Bhattacharyya and Johnson, 1977). The test statistic S_N is the number of success in N trials and therefore has a binomial distribution $b(N, .5)$ under H with success probability of ½ [3]. This distribution is given by the following formula

$$P_H(S_N = a) = \binom{N}{a}\frac{1}{2^N} \qquad for\ a = 0,1,2, \ldots\ldots N \qquad (4.1)$$

Therefore, with large N, the binomial distribution $b(N, .5)$ is approximately normal with a mean of $N/2$ and variance of $N/4$. Hence, under H for large sample approximation to the sign test, we need to compute

$$\frac{S_N - \frac{N}{2}}{\sqrt{\frac{N}{4}}} \sim N(0,1) \qquad (4.2)$$

the above limit theorem states that the distribution is approximately distributed as standard normal distribution.

4.2 *Results and Analysis*

In this research, the experimental data shown above was used in matlab to perform the statistical sign test and derive the necessary indices for all 80 images obtained from (Brodatz, 1966); the data is shown in Tables 1. Furthermore, remember that in Chapter 3 above and from Figure 5 it is clearly shown that each of the "Y" and "N" were converted to binary "1" and "0" respectively for feasible use in the statistical sign test. However, in addition to "0" signifying *no difference* among the images; recall that the test subjects marked an "X" (i.e. -1 in binary) if they weren't sure if any real difference existed among the images. As a result, to facilitate the use of the sign test, -1 was used to also represent "*no difference*" just as 0. Therefore, either both 0 and -1 represents *no significant difference,* while 1 represents a significant difference and as the sign test suggest, the test statistics is the sum of these counts (1, 0 and-1).

A first glance at the table of indices below clearly shows that majority of the images for all three bit levels have negative indices; thus the null hypothesis seems to be accepted. In order to fully understand the results of this experiment we need to consider that these indices are approximated as a normal distribution, which is beyond the upper boundary of 1.645. To analyze the data in Table 1, we will use the boundary to measure where the indices of the images fall. In other words, we will only consider the upper boundary (1.645) as a threshold to analyze the indices with respect to the null hypothesis, since our sign test statistic calculates S_N to be the number of 1's (i.e. significant difference). If an index is greater than our significance level (1.645) then the null hypothesis is rejected; the smaller the values the more significant the results will be.

Closely analyzing the table revealed that image D22 using a 3-bit encoding has a positive index of 2.54 passing the 1.645 boundary. Reading further down the table the image Lenna (3 bits) also demonstrated a similar effect, having an index of 1.97. The sign test results show that no similar effect exists among the 80 images encoded with 4 bits (16 levels). However, looking at the 5-bit encoded images the indices show that two particular image share the same effect as those of the 3-bit images. These images include D39 and D63 both with indices of 1.69 and 1.97 respectively. In total these 4 images where the only images out of the 80 used, that showed a significant difference. Figure 6 below illustrates these images alongside their originals.

In addition, the remainder of the indices demonstrates that majority of the images show very little difference, if not "no significant" difference from the original. Hence, the major goal of this experiment, to be able to show that images don't necessarily require an 8-bit representation, they can be easily depicted using 4 or 5 bit encoding. A more in depth analysis of the indices for each bit level confirms that the majority for all 3 levels of encoding fall under the 1.645 boundary. The images with 3-bit representation revealed that a total number of 78 images out of the 80 images used had indices under the bound, only D22 and Lenna with 3-bit coding show a significant difference. Moreover, the 4-bit images had all indices under the 1.645 upper bound, suggesting that a 4-bit encoding would be the most adequate level to represent an image. The images with a 5-bit representation showed all indices except D39 and D63 are under the bound 1.645.

Table 1: Indices of Images 1 to 80

Level\Image	D01	D02	D03	D04	D05	D06	D07	D08	D09	D10
3 bit	-1.13	1.41	0.28	-1.70	-0.57	-0.85	-0.57	-2.83	-1.13	1.41
4 bit	-0.28	-2.83	-3.39	-0.57	0.00	0.00	1.41	-0.85	-0.85	-2.55
5 bit	-4.24	-3.68	-3.11	-2.83	-1.98	-1.70	-1.98	-2.26	-1.98	-2.26

Level\Image	D11	D12	D13	D14	D15	D16	D17	D18	D19	D20
3 bit	-0.85	-0.28	-0.57	-0.57	0.57	-1.13	-1.13	-0.85	-1.13	-1.98
4 bit	-0.28	-1.13	-0.28	-0.85	-1.98	0.28	-0.28	0.57	-0.28	-1.70
5 bit	-0.85	-3.11	-1.13	-1.98	-1.13	-1.98	-1.70	-1.98	-2.55	-1.13

Level\Image	D21	D22	D23	D24	D89	D26	D27	D28	D29	D30
3bit	-0.85	2.55	-1.41	-0.57	0.00	-1.98	0.85	0.57	-0.85	-1.13
4bit	-1.98	-2.83	-1.41	-1.70	-1.70	-0.28	-1.70	-0.85	-0.57	-2.55
5bit	-3.96	-1.41	-1.41	-1.98	-3.39	-0.85	-2.83	-1.13	-2.83	-2.83

Level\Image	D31	D79	D88	D90	D35	D36	D37	D38	D39	D40
3bit	1.13	-0.28	-0.85	-1.41	-2.26	-1.13	0.00	0.85	-1.41	-0.85
4bit	-0.57	0.00	-0.85	-0.85	-1.98	-1.13	-1.41	-2.83	-1.70	-0.57
5bit	-1.41	-1.98	-1.41	-2.55	-1.70	-2.26	-2.55	-2.26	1.70	-0.85

Level\Image	D41	D42	D43	D44	D45	D46	D47	D48	D49	D50
3bit	-0.28	0.57	-1.98	-2.55	-2.55	-2.55	-1.70	-0.28	0.57	0.57
4bit	-0.57	0.57	-1.98	-1.41	-1.98	-2.83	-0.85	-1.13	-2.26	-2.26
5bit	-1.70	0.00	-2.55	-1.41	-2.83	-1.13	-2.26	-2.55	-0.85	-2.83

Level\Image	D51	D52	D53	D54	D55	D56	D57	D58	D59	D60
3bit	0.28	-1.41	-2.55	-0.85	-1.70	-1.13	-1.41	0.85	-1.41	-1.41
4bit	-1.13	-1.41	-1.70	-1.41	-1.13	-1.13	-2.55	-2.83	0.28	-1.70
5bit	-1.13	-1.13	-2.83	-2.26	-3.11	-1.70	-2.55	-2.26	1.13	-1.13

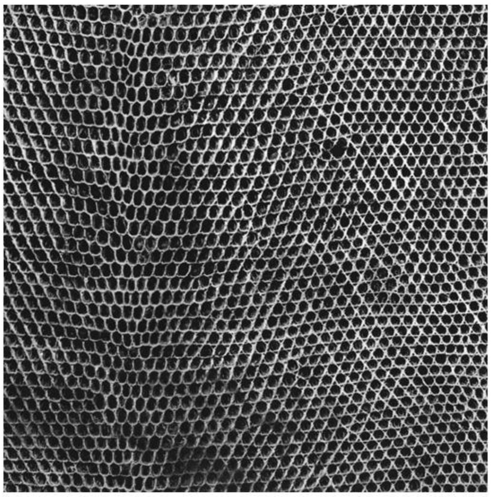
Level\Image	D61	D62	D63	D64	D65	D66	D67	D68	D69	D70
3bit	-0.28	-0.57	-1.98	-0.57	-1.98	-1.13	-0.28	-1.70	-2.26	-0.85
4bit	-0.57	-0.85	-1.41	0.00	-0.28	-0.85	-0.85	-1.70	1.13	0.57
5bit	-1.13	-2.26	1.98	-1.98	-2.83	-2.26	-0.85	-3.39	0.28	-1.13

Level\Image	D71	D72	D73	D74	D75	D76	Lenna	Fingerprint	Koala	Mandrill
3bit	-1.41	0.00	-1.41	0.28	-0.28	-0.57	1.98	-0.28	0.85	0.85
4bit	-0.57	-0.85	-1.13	-0.85	-2.26	-0.85	0.28	-0.85	1.41	-0.28
5bit	-0.57	-2.55	-1.70	-0.57	-2.26	-1.13	1.41	-0.85	-0.85	0.85

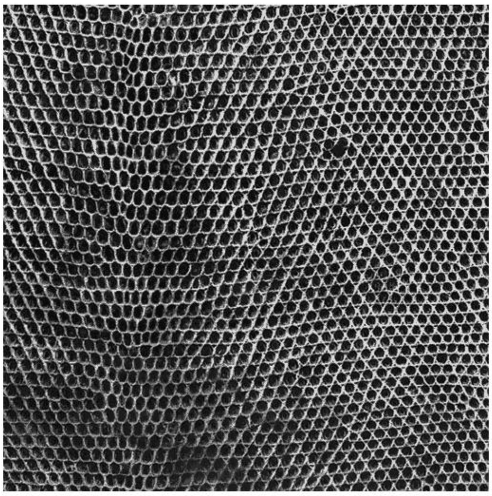
Conclusively, based on this survey the results revealed that majority of the test subjects believe that 78 of the images with both 3 and 5 bit representations showed the least significant difference from the original images. Hence, the sign test indicates that the null hypothesis, *H*, has been accepted, since majority of the images show no real significant difference.

Therefore, it can be confidently said that an image does not always require an 8-bit representation (256 gray levels), but rather it is adequately enough to represent an image using a 3-bit (16 gray levels) or 5-bit (32 gray levels) representation, without having the least signs of false contouring or rough edges.

A



Original



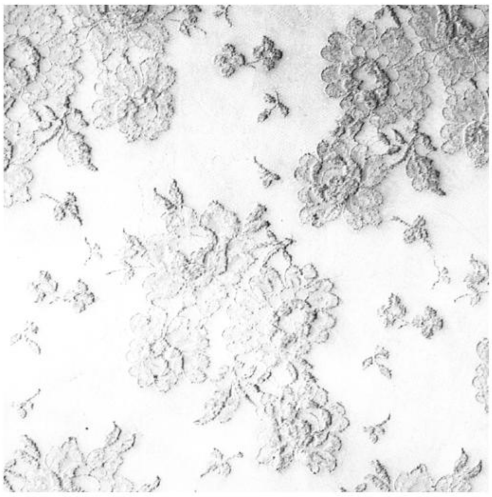
3 – Bit (8 gray levels)

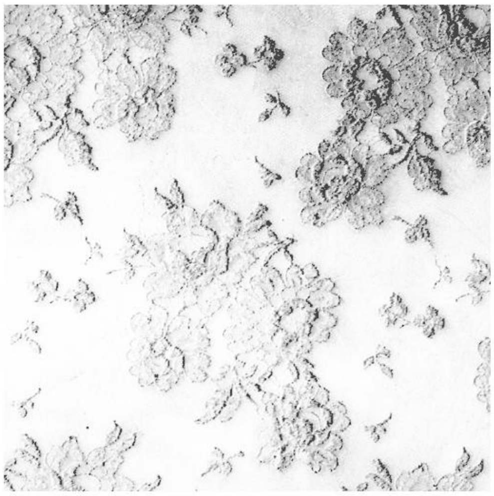
B

Original

3 – Bit (8 gray levels)

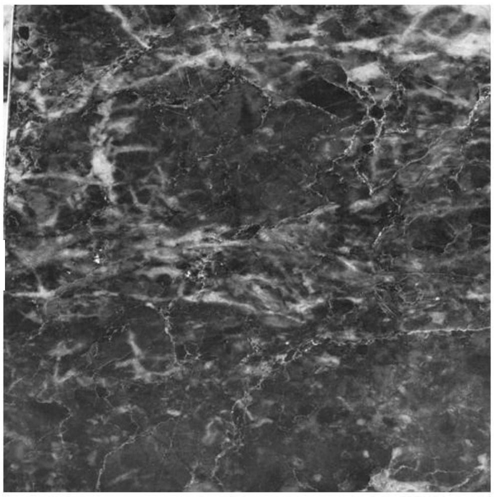
C

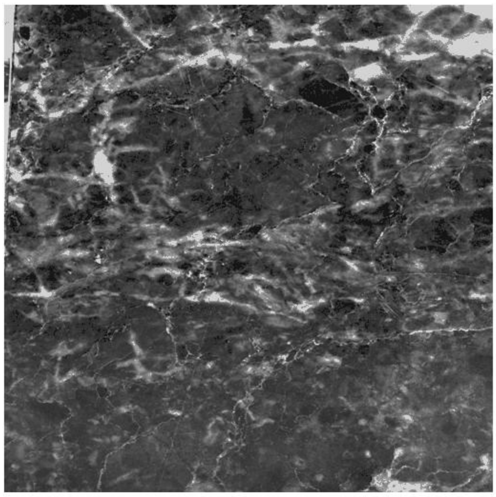




Original 5 – Bit (32 gray levels)

D





Original 5 – Bit (32 gray levels)

Figure 6: Images that showed significant difference: A-Image D22, B-Lenna, C–Image D39 and D- Image D63

The reason why D39 and D63 textures shown above do not pass a test of 32 levels but successfully interpret levels 8 and 16 are due to the special distributions of the original gray intensities as shown in Figure 7 which shows that the original texture images might be "over-fitted" by using 32 gray levels.

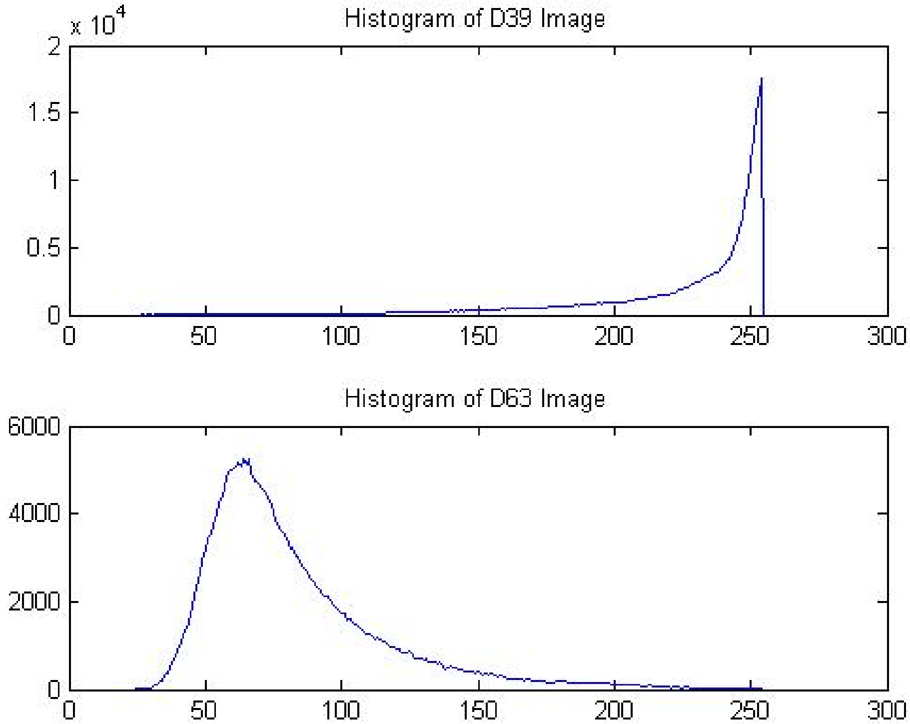


Figure 7: The distributions of gray intensities for images D39 and D63.

4.3. *Histogram Equalization vs. JPEG/JPEG2000 Image Compression*

The previous sections reveal that most of the texture images could be recorded in 8 gray levels without causing much visual difference, however, a natural image would take more levels. We further applied JPEG (Pennebaker and Mitchell, 1993) compression by Photoshop CS (Adobe Photoshop, 2009) and JPEG2000 based on 5/3 wavelet basis (Taubman and Marcellin, 2002; Chen, 2009) and report the peak signal-to-noise (PSNR) values for a comparison as shown in Figure 8 and Table 2, respectively.

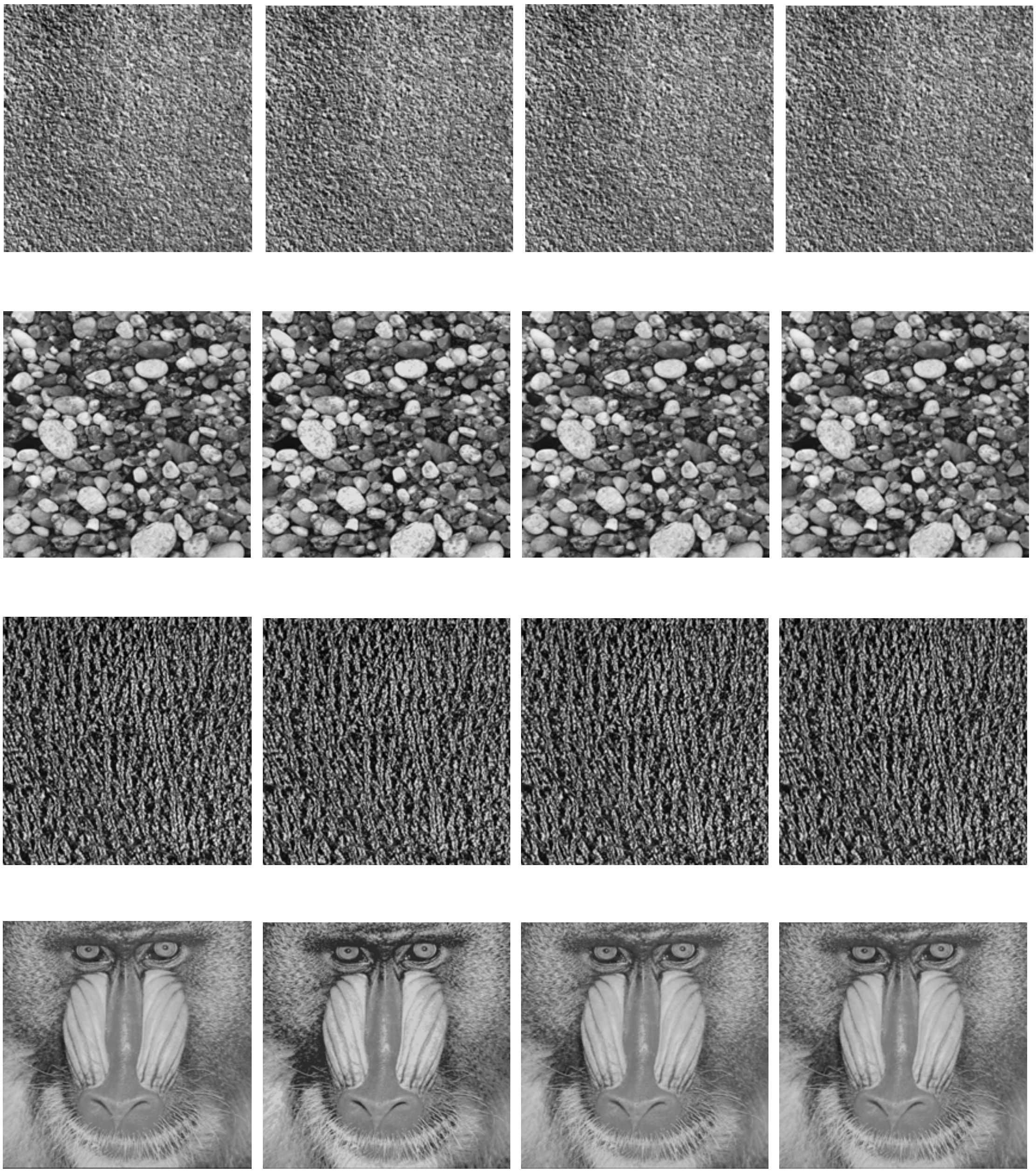


Figure 8: from left to right, an original image vs. results of histogram equalization (8 levels), JPEG by Photoshop (scale 2), JPEG2000 based on 5/3 transform for images D04: pressed cork, D23: beach pebbles, D24: calf leather, and Mandrill.

Table 2: Image representation vs. PSNR values for four 512x512 images: (a) pressed cork, (b) beach pebbles, (c) calf leather, (d) mandrill

Methods	D04	D23	D24	Mandrill
Histogram EQ PSNR	96 Kb 28.15	96 Kb 28.90	96 Kb 27.67	96 Kb 26.43
JPEG/DCT PSNR	118 Kb 24.60	75.7 Kb 29.39	121 Kb 24.81	67.6 Kb 27.40
JPEG2000/DWT PSNR	64 Kb 21.36	64 Kb 30.16	64 Kb 21.23	64 Kb 25.62

The images shown in Figure 8 associated with the statistics listed in Table 2 support that the results of visualization based on 8-level representation should be enough for most of textures due to the repeated "patterns" implicitly exist in a texture image even though the PSNR values are not high. This study only provides a statistical approach to verify visualization results, we do not take the homogeneous and/or correlation properties in a neighboring region of an image into account, a comparison with standard compression such as JPEG based on DCT (Pennebaker and Mitchell, 1993) and JPEG2000 based on wavelet transform (Taubman and Marcellin, 2002; Chen, 2009) is provided for reference but should not be emphasized.

5. Conclusion

This research study has clearly shown that in order to represent a texture image, it is not always necessary for an 8-bit encoding to be used. On the contrary, one can easily have the texture images represented at a minimum of a 3-bit coding. As the results shown in this paper, the proposed null hypothesis has been verified to be true. Results showed that the test subjects believe 78 out of 80 images or 97.5% of the images with 3 and 5 bit levels, at 5% of the rejection level showed no real significant difference when compared to their originals. Therefore, histogram equalization proves to effectively alter a texture image to many different levels of contrast, however, in order to obtain best and adequate results from the equalization method we can confidently suggest (based on this survey) that a texture image can be equalized and encoded using 3~5 bits without having the least sign of difference. We emphasize the representation of minimum levels for texture images but not optimal compression for general natural images. Whether the provided statistical approach could be adopted for the study of general natural images such as commonly used images lenna, scene, and etc. merits further investigation.

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