

4. Image Enhancement

The principle objective of image enhancement is to process an image so that the result is more suitable than the original image for a specific application. The word *specific* is important, because it establishes that the techniques are problem orientated. The methods and objectives vary with the application.

When images are enhanced for human viewers, as in television, the objective may be to improve the perceptual aspects: image quality, intelligibility or visual appearance. In other applications, such as object detection by a machine, an image may be preprocessed to aid machine performance. Because the objective of image enhancement is dependent on the application context, and the criteria for enhancement are often subjective or too complex to be easily converted into useful measures, image enhancement algorithms tend to be simple, qualitative and often ad-hoc. In addition, an image enhancement algorithm that performs well for one class of images may not perform as well for other classes.

Most of the approaches for image enhancement fall into two broad categories - *spatial domain* methods and *frequency domain* methods. The spatial domain refers to the image plane itself and approaches in this category are based on direct manipulation of pixels in an image. Frequency domain methods are based on modifying the Fourier transform of an image - for example filtering. This will be covered later in the course.

Spatial domain methods include:-

1. Simple Intensity Transformation
2. Histogram processing - equalisation and modification

1. Simple Intensity Transformations

1.1 Image Negatives

The idea is to reverse the order from black to white so that the intensity of the output image decreases as the intensity of the input increases. For example if the pixel value on the input image is r , it becomes $(L - 1) - r$ where L is the number of grey levels in the image. This is illustrated in figure 1.



Figure 1: (a) Input Image(b) Negative of input image

If the transformation is expressed in the form

$$s = T(r)$$

where T is a *gray level transformation*, and r is the input gray level and s is the output gray level of a point (x, y) , then the transformation can be expressed graphically as figure 2.

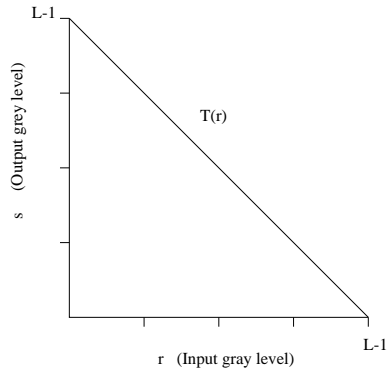


Figure 2: Gray level transformation function

1.2 Contrast Stretching

Low contrast images can result from poor illumination, lack of dynamic range in the imaging sensor or even wrong settings on the image acquisition sensor. The idea of contrast stretching is to increase the dynamic range of the grey levels in the image being processed.

Figure 3 shows a typical transformation used for contrast stretching. The locations of the points (r_1, s_1) and (r_2, s_2) , control the shape of the transformation function. If $r_1 = s_1$ and $r_2 = s_2$, the transformation is a linear function which produces no change.

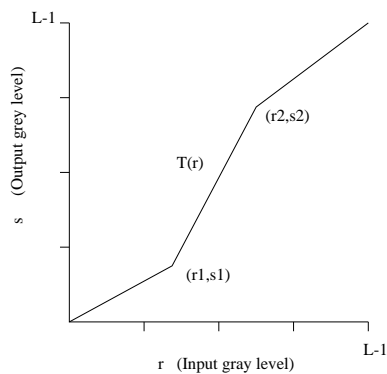


Figure 3: Form of Transformation Function

If $r_1 = r_2$ and $s_1 = 0$ and $s_2 = L - 1$, the transformation becomes a *thresholding function* that creates a binary image (only 2 grey levels). Figure 4 shows this function applied to the landsat image.

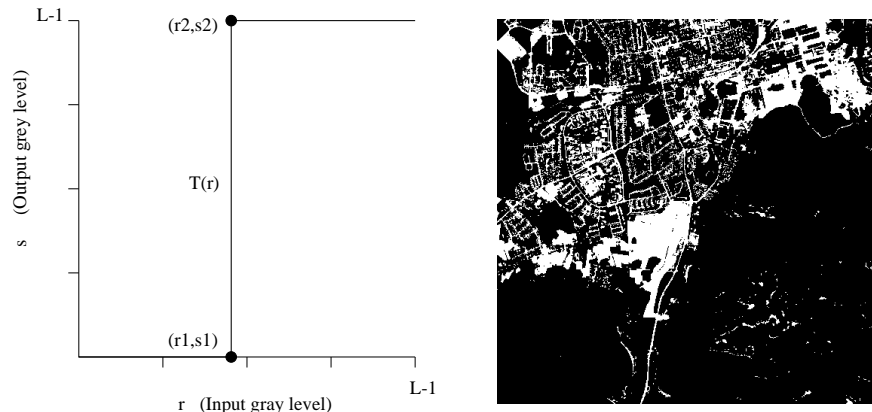


Figure 4: (a) Transformation Function (b) Threshold image

Intermediate values of (r_1, s_1) and (r_2, s_2) produce various degrees of spread in the gray levels of the output image, thus affecting its contrast. In general $r_1 \leq r_2$ and $s_1 \leq s_2$ is assumed so that the transformation function is single valued and monotonically increasing. This condition preserves the order of the grey levels and thus prevents intensity artifacts in the processed image. Figure 5 shows a transformation function applied to the landsat image.

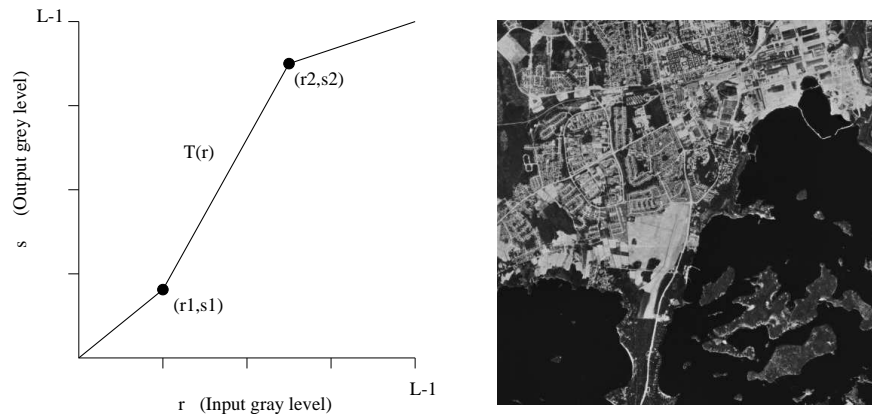


Figure 5: (a) Transformation Function (b) Result of contrast stretching

1.3 Compression of Dynamic Range

Sometimes the dynamic range of the processed image exceeds the capability of the display device and only the brightest parts of the image are visible. This has already been mentioned when trying to view the Fourier Transform of an image, where the range of values were compressed using the intensity transformation

$$s = c \log(1 + |r|)$$

where c is a scaling constant. This is illustrated in figure 6, where in this case the values of r ranged from 0 to 2.5×10^6 , but we wished to display the image using only 256 grey levels. This transformation function is illustrated in figure 7.

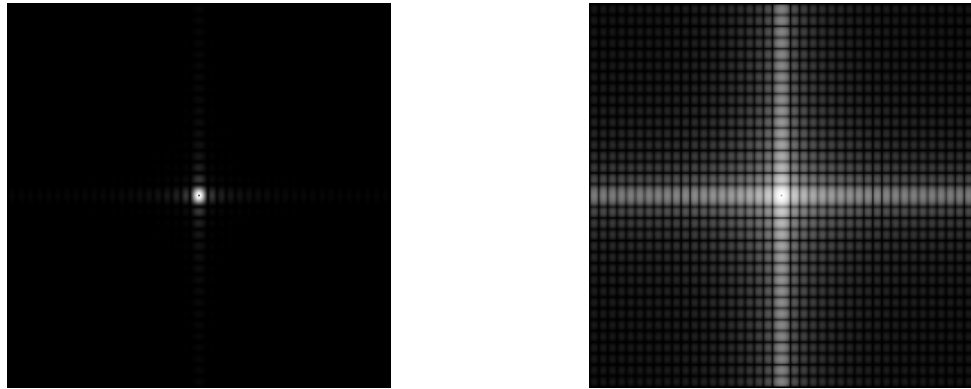


Figure 6: (a) Input image (c) compressed dynamic range

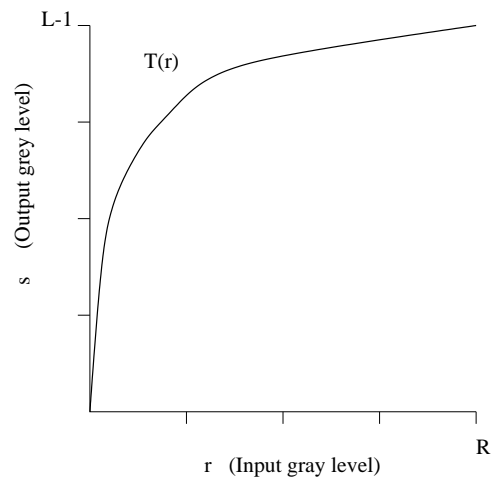


Figure 7: Logarithmic transformation function for compression of dynamic range.

2. The Image Histogram

Whilst many image operations are extremely 'computer intensive' in terms of the extraction of useful information from a given input much concerning the basic nature of the data can be obtained very simply and with minimum computation from the image histogram. In addition various mappings can be applied to the histogram levels in order to emphasize certain image features, neutralise the effects of sensor imperfections, *etc*, again in a relatively simple way.

The image histogram is basically a plot of the number of elements in the image having a particular value (typically grey scale values between 0 and 255). A typical example is shown in figure 8.

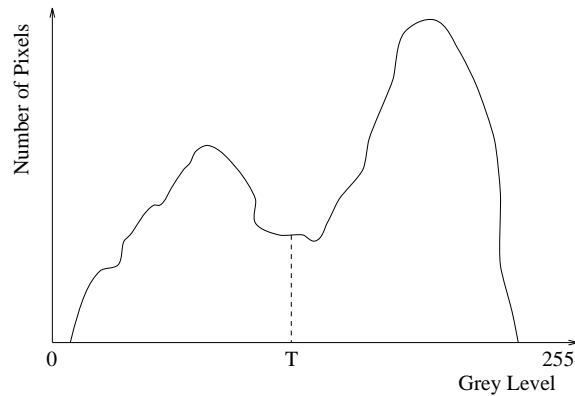


Figure 8: Image Histogram

Several features can be noted from this histogram:-

1. The distribution tapers off to zero at finite levels greater than zero and less than 255. The image digitisation process has not introduced any peak or minimum clipping, therefore, the occupied levels are satisfactorily distributed through the available range.
2. The histogram is typical of a natural scene, with a peak in the dark grey and another towards peak white with a fairly distinct valley in between.
3. A rudimentary separation between dark and light regions could be made by choosing a threshold at T and recording all pixels with amplitude less than T as black and all pixels with amplitude greater than T as white. This performs a rudimentary segmentation.

The following figures 9(a) and 9(b) demonstrate some of the defects of digitisation. In figure 9(a) the digitisation levels have been incorrectly set and severe peak clipping has occurred. This type of histogram corresponds to a bright image. The histogram in figure 9(b) has a severely reduced contrast range and corresponds to an image with little dynamic range and contrast.

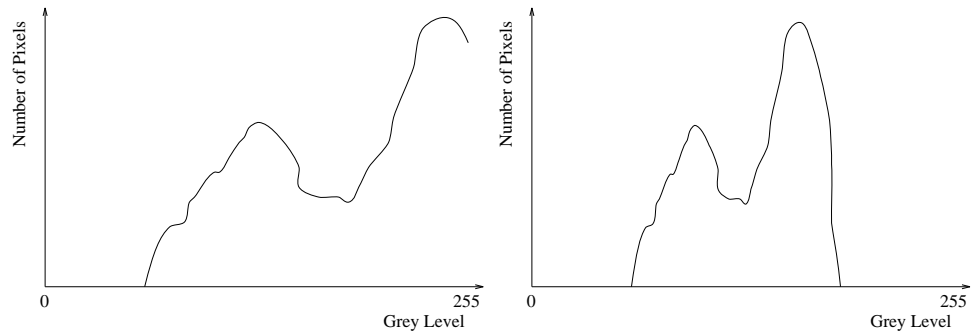


Figure 9: (a) Histogram with peak clipping (b) histogram with low contrast

One point to note is that the histogram of an image is unique, but the reverse of this statement is not true. Only one histogram can be created from an image but several different images could be re-created from the one histogram, since the histogram gives no indication about the location of the pixels just their grey scale values.

We will now examine various methods of modifying the histogram of an image.

2.1 The Histogram

The histogram of a digital image with grey levels in the range $[0, L-1]$ is a discrete function $p(r_k) = n_k/n$, where r_k is the k^{th} grey level, n_k is the number of pixels in the image with that grey level, n is the total number of pixels in the image and $k = 0, 1, 2, \dots, L-1$. Therefore $p(r_k)$ gives the probability of occurrence of grey level r_k .

2.2 Histogram Modification

Let the variable r represent the grey levels in the image to be enhanced. It is assumed that the grey levels have been normalised to lie in the range $[0, 1]$, with $r=0$ representing black and $r=1$ representing white.

For any r in the range $[0, 1]$, we consider transformations of the form

$$s = T(r)$$

which produce a level s for every pixel value r in the original image. It is assumed that the transformation function satisfies the following conditions

- (a) $T(r)$ is single valued and monotonically increasing in the interval $0 \leq r \leq 1$
- (b) $0 \leq T(r) \leq 1$ for $0 \leq r \leq 1$

The first condition preserves the order from black to white in the grey scale and the second condition guarantees a mapping that is consistent with the allowed range of pixel value. Figure 10 illustrates a transformation function satisfying these requirements.

The inverse transform from s back to r can be denoted

$$r = T^{-1}(s)$$

where T^{-1} also satisfies conditions (a) and (b).

An input level r maps onto an output level s and an adjacent level $r + \Delta r$ into $s + \Delta s$. All intervening levels between r and $r + \Delta r$ map into levels between s and $s + \Delta s$ and the number of pixels in

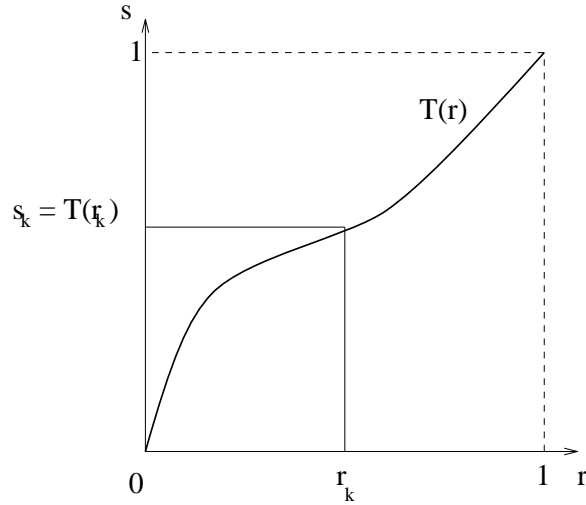


Figure 10: Grey Level Transformation Function

each case is the same, as are then the equivalent areas under the input probability density function $p(r)$ and the output probability density function $p(s)$. Thus

$$\int_r^{r+\Delta r} p(r)dr = \int_s^{s+\Delta s} p(s)ds$$

Approximately, then exactly in the limit

$$p(r)\Delta r \approx p(s)\Delta s$$

and so

$$p(s) \approx p(r) \frac{\Delta r}{\Delta s} = \left[p(r) \frac{dr}{ds} \right]_{r=T^{-1}(s)}$$

The following enhancement techniques are based on modifying the appearance of an image by controlling the probability density function of its grey levels via the transformation function $T(r)$.

2.3 Histogram Equalisation

The general solution of the histogram transformation problem is not always possible in the continuous case (approximations can always be made in the discrete case) but there is one particular transformation which produces an important result for applications involving the comparison of images digitised under different conditions. This particular transformation produces an approximation to a uniform histogram for the image in question and its application is known as *histogram equalisation*.

Consider the transformation function

$$s = T(r) = \int_0^r p(x)dx \quad 0 \leq r \leq 1 \quad (1)$$

where x is a dummy variable of integration and the input range is normalised so that r is in the

range $0 \leq r \leq 1$. The rightmost side of equation 1 is simply the Cumulative Distribution Function (CDF) of r . Conditions (a) and (b) presented earlier are satisfied by this transformation function since the CDF increases monotonically from 0 to 1 as a function of r .

Differentiating equation 1

$$\frac{ds}{dr} = p(r) \tag{2}$$

Considering again the equation

$$p(s) = \left[p(r) \frac{dr}{ds} \right]_{r=T^{-1}(s)}$$

and substituting in equation 2

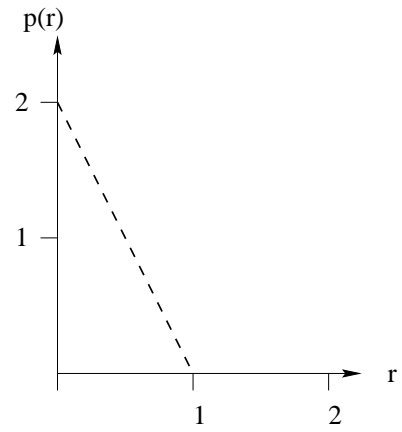
$$p(s) = \left[p(r) \frac{1}{p(r)} \right]_{r=T^{-1}(s)} = [1]_{r=T^{-1}(s)} = 1$$

which is a uniform density in the interval of definition of the transformed variable s ($0 \leq s \leq 1$).

2.3.1 Example - Continuous PDF

Calculate the transformation function for the following continuous probability density function and prove that application of this transformation will produce a uniform histogram.

$$p(r) = \begin{cases} -2r + 2 & \text{if } 0 \leq r \leq 1 \\ 0 & \text{elsewhere} \end{cases}$$



2.4 Discrete Histogram

In order to be useful for image processing, the concepts developed previously must be formulated in a discrete form. For grey levels that take on discrete values, we deal with the probabilities

$$P(r_k) = \frac{n_k}{n} \quad 0 \leq r_k \leq 1 \quad \text{and} \quad k = 0, 1, 2, \dots, L-1$$

where L is the number of grey levels, $p(r_k)$ is the probability of the k^{th} grey level, n_k is the number of times this level appears in the image.

The discrete form of equation 1 is

$$\begin{aligned} s_k = T(r_k) &= \sum_{j=0}^k \frac{n_j}{n} \\ &= \sum_{j=0}^k p(r_j) \quad 0 \leq r_k \leq 1 \quad \text{and} \quad k = 0, 1, 2, \dots, L-1 \end{aligned}$$

The inverse transformation is denoted

$$r_k = T^{-1}(s_k) \quad 0 \leq s_k \leq 1$$

where both $T(r_k)$ and $T^{-1}(s_k)$ are assumed to satisfy conditions (a) and (b). The transformation function $T(r_k)$ can be calculated directly from the image.

2.5 Example - Discrete Histogram

Suppose a 64 by 64 pixel 3 bit digital image has the following grey level distribution. Calculate the transformation required to produce as close to a uniform histogram as possible, and give the new distribution of grey levels.

Grey Level	0	1	2	3	4	5	6	7
Number of Pixels	790	1023	850	656	329	245	122	81

2.6 Example Images

The usefulness of histogram equalisation is illustrated in figure 11. Figure 11(a) shows a landsat image which is dark with very little dynamic range. Figure 11(c) then shows the result of applying the histogram equalisation techniques to this image. A further example is shown in figure 12

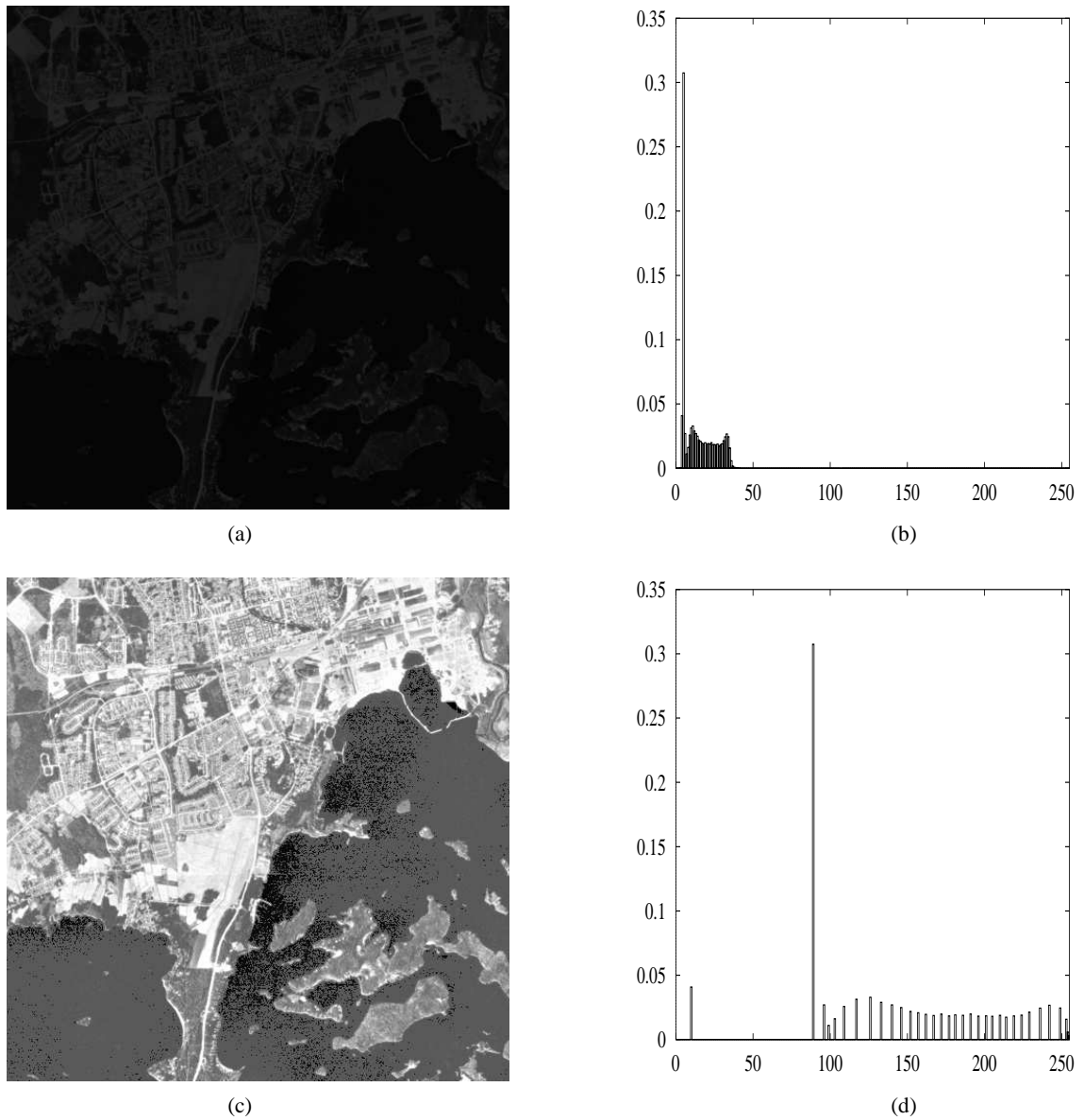
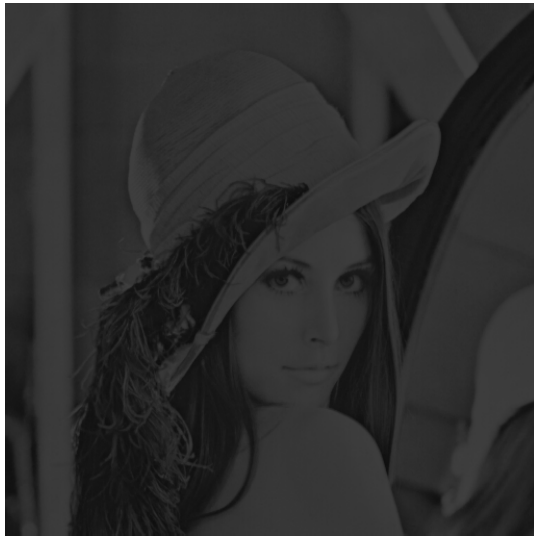
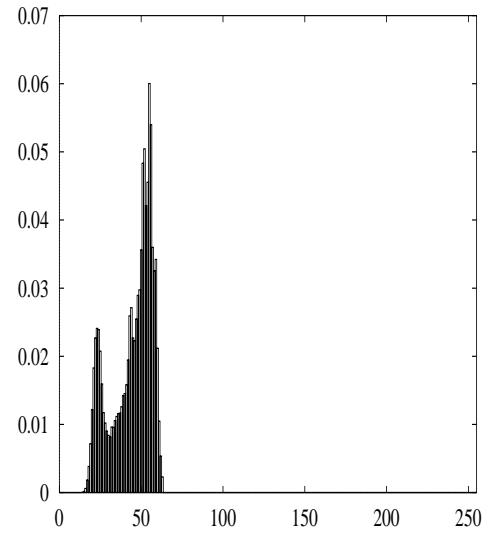


Figure 11: (a) Original image (b) histogram of original image (c) image after histogram equalisation (d) histogram of equalised image



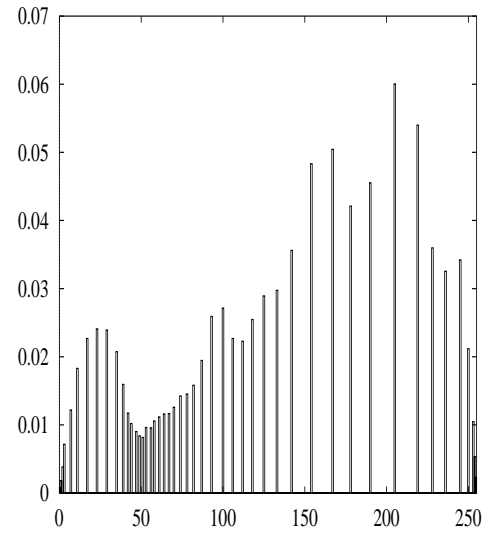
(a)



(b)



(c)



(d)

Figure 12: (a) Original image (b) histogram of original image (c) image after histogram equalisation (d) histogram of equalised image

2.7 Histogram Specification

Although the histogram equalisation method is quite useful, it does not lend itself to interactive image enhancement applications. This is because the method is only capable of generating one result: an approximation to a uniform histogram.

Sometimes the ability to specify particular histogram shapes capable of highlighting certain grey level ranges in an image is desirable. This is the process of *histogram specification* and the technique is developed as follows. The first step is to apply the histogram equalisation as described above, *ie*

$$s = T(r) = \int_0^r p(x)dx$$

In the same way the desired output data z , (if it was available) could be processed to yield a uniform histogram using

$$v = G(z) = \int_0^z p(y)dy$$

The levels in the desired image, z , could then be obtained from the inverse process

$$z = G^{-1}(v)$$

Since both $p(s)$ and $p(v)$ are the same (uniform) density, the same result is achieved by using the inverse transform of s instead of v .

In summary the procedure can be summarised as

1. Equalise the levels of the original image
2. Specify the desired density function and obtain the transformation function $G(z)$
3. Apply the inverse transformation function, $z = G^{-1}(s)$, to the levels obtained in step 1.

This process yields a processed version of the original image, with the new grey levels characterised by the specified density $p(z)$.

Whilst in the continuous case the inverse function G^{-1} may be difficult, or impossible, to obtain, with digital images the number of separate levels is small enough to calculate a mapping for each of them.

Although the method of histogram specification involves two transformation functions

$$s = T(r)$$

and

$$z = G^{-1}(s)$$

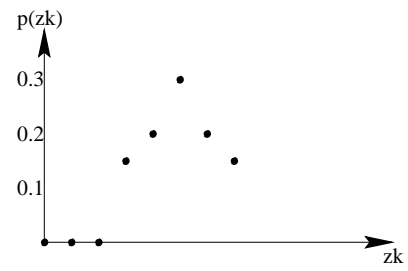
These can be combined into one function that yields the desired levels

$$z = G^{-1}[T(r)]$$

2.8 Specification Example

The previous example considered the equalisation of an image histogram. This example will consider the same input histogram but specifies the output histogram to have the form:-

z_k	$p(z_k)$
0	0.0
1	0.0
2	0.0
3	0.15
4	0.20
5	0.30
6	0.20
7	0.15



In conclusion it may be noted that there are alternative approaches to the problem of histogram modification. For example, it is possible to apply such techniques in a sectional manner with different parameters over different parts of a single image. Although, in this case attention must be given to the problem of discontinuities which are likely to appear at the boundaries between sections.

The histogram modification method can also be applied to colour images.