



Medical Image Enhancement Using Pixel Operation

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Abstract: Medical image is never the correct representation of the object under observation; it is always ruined by degradations during acquisition and within the imaging system itself. These include noise, distortion and smudge. Enhancement of such corrupted images is an important and challenging issue in medical image processing. These pixel operations on medical imaging have their own assumptions, advantages and disadvantages. This paper has been discussed and applied the various pixel operations techniques for the removal of noise from the medical images.

Keywords: Medical imaging, histogram, noise, dynamic range, intensity scaling.

I. INTRODUCTION

Image enhancement techniques are used to refine a given image so that desired image features become easier to perceive for the human visual system or more likely to be detected by automated image analysis systems [1, 13]. Image enhancement allows the observer to see details in images that may not be immediately observable in the original image. This may be the case, for example, when the dynamic range of the data and that of the display are not commensurate, when the image has a high level of noise, or when contrast is insufficient [4, 5, 8, 9]. Fundamentally, image enhancement is the transformation or mapping of one image to another [10, 14]. This transformation is not necessarily one-to-one, so two different input images may transform into the same or similar output images after enhancement. More commonly, one may want to generate multiple enhanced versions of a given image. This aspect also means that enhancement techniques may be irreversible. Often the enhancement of certain features in images is accompanied by undesirable effects. Valuable image information may be lost, or the enhanced image may be a poor representation of the original. Furthermore, enhancement algorithms cannot be expected to provide information that is not present in the original image. If the image does not contain the feature to be enhanced, noise or other unwanted image components may be inadvertently enhanced without any benefit to the user.

II. PRELIMINARIES AND DEFINATION

We define a *digital image* as a two-dimensional array of numbers that represent the real, continuous

intensity distribution of a spatial signal. The continuous spatial signal is sampled at regular intervals, and the intensity is quantized to a finite number of levels. Each element of the array is referred to as a *picture element* or *pixel*. The digital image is defined as a spatially distributed intensity signal $f(m, n)$, where f is the intensity of the pixel, and m and n define the position of the pixel along a pair of orthogonal axes usually defined as horizontal and vertical. We shall assume that the image has M rows and N columns and that the digital image has P quantized levels of intensity (gray levels) with values ranging from 0 to $P - 1$. The histogram of an image, commonly used in image enhancement and image characterization, is defined as a vector that contains the count of the number of pixels in the image at each gray level.

III. PIXEL OPERATIONS

This methods of image enhancement is depend only on the pixel gray level and do not take into account the pixel neighborhood or whole-image characteristics.

A. Compensation for Nonlinear Characteristics of Display or Print Media

Digital images are generally displayed on cathode ray tube (CRT) type display systems or printed using some type of photographic emulsion. Most display mechanisms have nonlinear intensity characteristics that result in a nonlinear intensity profile of the image when it is observed on the display. This effect can be described succinctly by the equation

$$e(m, n) = C(f(m, n)),$$

where $f(m, n)$ is the acquired intensity image, $e(m, n)$ represents the actual intensity output by the display

system, and $C()$ is a nonlinear display system operator. In order to correct for the nonlinear characteristics of the display, one must apply a transform that is the inverse of the display's nonlinearity [14, 16]

$$g(m, n) = T(e(m, n)) = C^{-1}(C(f(m, n)))$$

$$g(m, n) = f(m, n).$$

where $T()$ is a nonlinear operator that is approximately equal to $C^{-1}()$, the inverse of the display system operator, and $g(m, n)$ is the output image. Determination of the characteristics of the nonlinearity could be difficult in practice. In general, if a linear intensity wedge is imaged, one can obtain a test image that captures the complete intensity scale of the image acquisition system. However, an intensity measurement device that is linear is then required to assess the output of the display system, in order to determine its actual nonlinear characteristics.

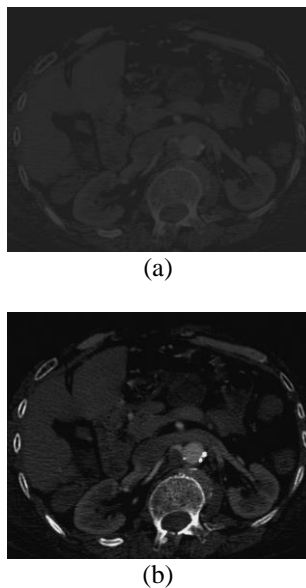


FIGURE 1 (a) Original image as seen on a poor-quality CRT-type display. This image has poor contrast, and details are difficult to perceive. (b) The nonlinearity of the display is reversed by the transformation, and structural details become more visible

A slightly exaggerated example of this type of a transform is presented in Figure 1. Figure 1a presents a simulated CRT display with a logarithmic characteristic. This characteristic tends to suppress the dynamic range of the image decreasing the contrast. Figure 1b presents the same image after an inverse transformation to correct for the display nonlinearity. Although these operations do in principle correct for the display, the primary mechanism for review and analysis of image information is the human visual system, which is fundamentally a nonlinear reception system and adapts locally to the intensities presented.

B. Intensity Scaling

Intensity scaling is a method of image enhancement that can be used when the dynamic range of the acquired image data significantly exceeds the characteristics of the display system, or vice versa. It may also be the case that image information is present in specific narrow intensity bands that may be of special interest to the observer. Intensity scaling allows the observer to focus on specific intensity bands in the image by modifying the image such that the intensity band of interest spans the dynamic range of the display [

14, 16]. For example, if f_1 and f_2 are known to define the intensity band of interest, a scaling transformation may be defined as

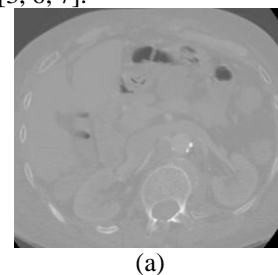
$$e = \begin{cases} f & f_1 \leq f \leq f_2 \\ 0 & \text{otherwise} \end{cases}$$

$$g = \frac{e - f_1}{f_2 - f_1} \cdot (f_{max}),$$

where e is an intermediate image, g is the output image, and f_{max} is the maximum intensity of the display. These operations may be seen through the images in Figure 2. Figure 2a presents an image with detail in the intensity band from 180 to 210. The image, however, is displayed such that all gray levels in the range 0 to 255 are seen. Figure 2b shows the histogram of the input image, and Figure 3(a) presents the same image with the 180 to 210 intensity band stretched across the output band of the display. Figure 3(d) shows the histogram of the output image with the intensities that were initially between 180 and 210 but are now stretched over the range 0 to 255. The detail in the narrow band is now easily perceived; however, details outside the band are completely suppressed.

C. Histogram Equalization

Define although intensity scaling can be very effective in enhancing image information present in specific intensity bands, often information is not available *a priori* to identify the useful intensity bands. In such cases, it may be more useful to maximize the information conveyed from the image to the user by distributing the intensity information in the image as uniformly as possible over the available intensity band [3, 6, 7].



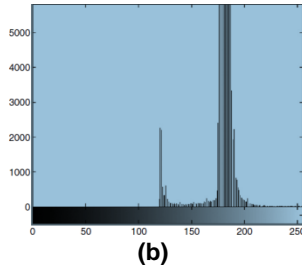


FIGURE 2 (a) Input image where details of interest are in the 180–210 gray level band. This intensity band provides an example of a feature that may be of clinical interest. (b) Histogram of the input image in (a).

This approach is based on an approximate realization of an information-theoretic approach in which the normalized histogram of the image is interpreted as the probability density function of the intensity of the image. In histogram equalization, the histogram of the input image is mapped to a new maximally flat histogram.

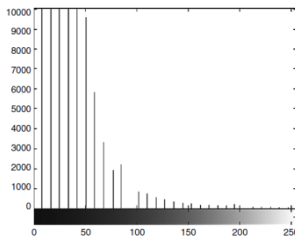


FIGURE 3 (a) This output image selectively shows the intensity band of interest stretched over the entire dynamic range of the display. This specific enhancement may be potentially useful in highlighting features or characteristics. (b) Histogram of the output image in (a). This histogram shows the gray level in the original image in the 180–210 intensity band stretched over to 0 to 255

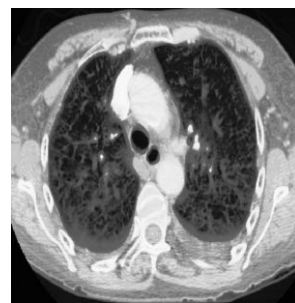
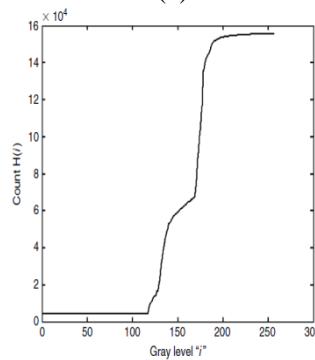
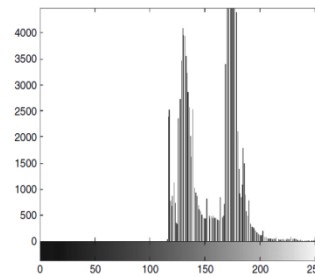
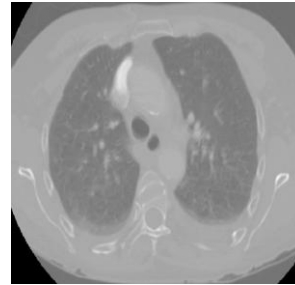
Histogram is defined as $h(i)$, with 0 to $P - 1$ gray levels in the image.

$$h(i) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \delta(f(m, n) - i), \quad i = 0, \dots, p - 1$$

$$\text{Where } \delta(w) = \begin{cases} 1 & w = 0, \\ 0 & \text{otherwise} \end{cases}$$

The total number of pixels in the image, $M*N$, is also the sum of all the values in $h(i)$. Thus, in order to distribute most uniformly the intensity profile of the image, each bin of the histogram should have a pixel count of $(M*N)/P$. It is, in general, possible to move

the pixels with a given intensity to another intensity, resulting in an increase in the pixel count in the new intensity bin. On the other hand, there is no acceptable way to reduce or divide the pixel count at a specific intensity in order to reduce the pixel count to the desired $(M*N)/P$. In order to achieve approximate uniformity, the average value of the pixel count over a number of pixel values can be made close to the uniform level.



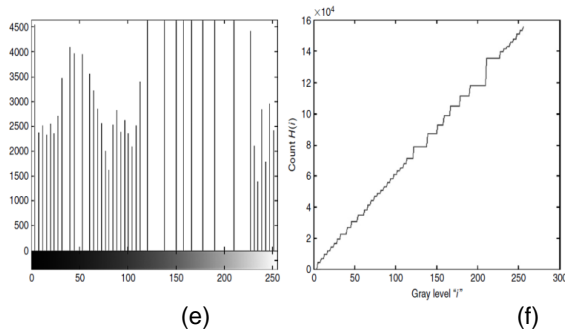


FIGURE 4 (a) Original image (b) Histogram of the original image. (c) Cumulative histogram of the original image in (a). (d) Histogram-equalized image.(e) Histogram of the enhanced image in (d). (f) Cumulative histogram of the enhanced image in (d)

A simple and readily available procedure for redistribution of the pixels in the image is based on the normalized cumulative histogram, defined as

$$H(i, j) = \frac{1}{M \cdot N} \sum_{l=0}^j h(i, l), j = 0, 1, \dots, p-1$$

The normalized cumulative histogram can be used as a mapping between the original gray levels in the image and the new gray levels required for enhancement. The enhanced image $g(m, n)$ will have a maximally uniform histogram if it is defined as

$$g(m, n) = (P - 1) \cdot H(f(m, n))$$

Figure 4(a) presents an original CT image where the gray levels are not uniformly distributed, while the associated histogram and cumulative histogram are shown in Figures 4(b) and 1.3c, respectively. The cumulative histogram is then used to map the gray levels of the input images to the output image shown in Figure 1.3d. Figure 1.3e presents the histogram of Figure 1.3d, and Figure 1.3f shows the corresponding cumulative histogram. Figure 1.3f should ideally be a straight line from (0, 0) to $(P - 1, P - 1)$, but in fact only approximates this line to the extent possible given the initial distribution of gray levels.

IV RESULT AND DISCUSSION

Fig 4 (a) is the original image where gray levels are not uniformly distributed. From the image it has been cleared that many image details are not well visualized because of the low contrast. Fig4(b) is the histogram of the original image in 4(a). Note the nonuniformity of the histogram.4(c) Cumulative histogram of the original image in (a). This part was improved by applying histogram equalization

techniques on the original image. In fig4(d) Contrast is enhanced so that subtle changes in intensity are more readily observable. Fig (e) shows the histogram of the enhanced image in 4(d). Note the distribution of intensity counts that are greater than the mean value have been distributed over a larger gray-level range. Hence it is conclude that the pixel operations are very useful for enhancing the image quality of the medical images for better diagnosis of the patient.

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