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Image Enhancement : A Pre-Processing Technique

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Abstract

An image can be synthesized from a micrograph of various cell organelles by assigning a light intensity value to each cell organelle. The sensor signal is "digitized"— converted to an array of numerical values, each value representing the light intensity of a small area of the cell.

Digital image processing is an area characterized by the need for extensive experimental work to establish the viability of proposed solutions to a given problem. Image processing modifies pictures to improve them, extract information, and change their structure.

Image enhancement improves the quality (clarity) of images for human viewing. Removing blurring and noise, increasing contrast, and revealing details are examples of enhancement operations. For example, an image might be taken of an endothelial cell, which might be of low contrast and somewhat blurred. Reducing the noise and blurring effect and increasing the contrast range could enhance the image. The original image might have areas of very high and very low intensity, which mask details.

Key words: histogram equalization, grey values, dft, Fourier transform

1. Introduction

Digital image processing is an area characterized by the need for extensive experimental work to establish the viability of proposed solutions to a given problem.

Image processing modifies pictures to improve them (enhancement, restoration), extract information (analysis, recognition), and change their structure (composition, image editing). Images can be processed by optical, photographic, and electronic means, but image processing using digital computers is the most common method because digital methods are fast, flexible, and precise.

An image can be synthesized from a micrograph of various cell organelles by assigning a light intensity value to each cell organelle. The sensor signal is "digitized"--converted to an array of numerical values, each value representing the light intensity of a small area of the cell. The digitized values are called picture elements, or "pixels," and are stored in computer memory as a digital image. A typical size for a digital image is an array of 512 by 512 pixels, where each pixel has value in the range of 0 to 255. The digital image is processed by a computer to achieve the desired result.

Image enhancement improves the quality (clarity) of images for human viewing. Removing blurring and noise, increasing contrast, and revealing details are examples of enhancement operations. For example, an image might be taken of an endothelial cell, which might be of low contrast and somewhat blurred. Reducing the noise and blurring and increasing the contrast range could enhance the image. The original image might have areas of very high and very low intensity, which mask details. An adaptive enhancement algorithm reveals these details. Adaptive algorithms adjust their operation based on the image information (pixels) being processed. In this case the mean intensity, contrast, and sharpness (amount of blur removal) could be adjusted based on the pixel intensity statistics in various areas of the image.

Image processing technology is used by planetary scientists to enhance images of Mars, Venus, or other planets. Doctors use this technology to manipulate CAT scans and MRI images. Image processing in the laboratory can motivate students and make science relevant to student learning. Image processing is an excellent topic for classroom application of science research techniques.

One of part of the image processing is the image enhancement. Image enhancement is the improvement of digital image quality, without knowledge about the source of degradation. If the source of degradation is known, one calls the process image restoration. Both are *iconical* processes, viz. input and output is images. The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application.

2. *Image Enhancement :*

Image enhancement approaches fall into two broad categories: spatial domain methods and frequency domain methods. The term *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* processing techniques are based on modifying the Fourier transform of an image.

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide 'better' input for other automated image processing techniques.

Image enhancement techniques can be divided into two broad categories:

1. Spatial domain methods, which operate directly on pixels, and

2. Frequency domain methods, which operate

on the Fourier transform of and image.

2.1. *Spatial domain methods :*

The value of a pixel with coordinates (x, y) in the enhanced image F is the result of performing some operation on the pixels in the neighborhood of (x, y) in the input image, F. Neighborhoods can be any shape, but usually they are rectangular.

2.1.1. *Grey scale manipulation :*

The simplest form of operation is when the operator T acts only on a 1×1 pixel neighborhood in the input image, that is $\hat{F}$ (x, y) depends on the value of F only at (x, y). This is a grey scale transformation or mapping. The simplest case is thresholding where the intensity profile is replaced by a step function, active at a chosen threshold value. In this case any pixel with a grey level below the threshold in the input image gets mapped to 0 in the output image. Other pixels are mapped to 255.

Other grey scale transformations are outlined in Figure 1 below.

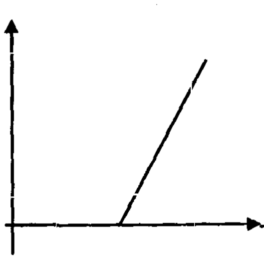

Fig1.a.Darkening

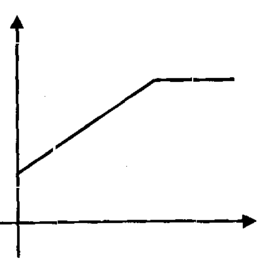

Fig1.b.Lightning

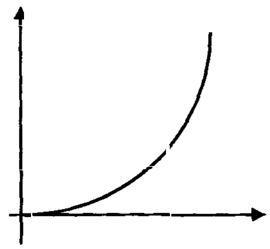

Fig.1.c. Emphasis Light

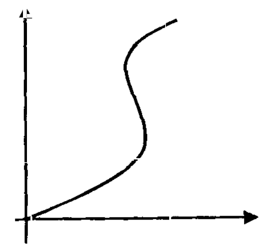

Fig.1.d. High Contrast

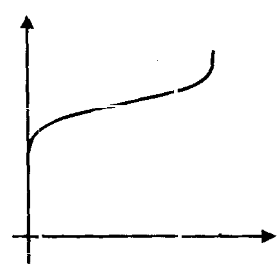

Fig.1.d. Low Contrast

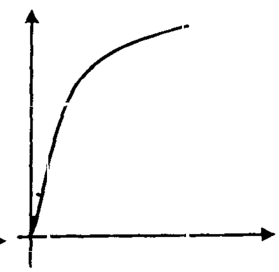

Fig.1.e. Emphasize shadows

2.1.2. *Histogram Equalization :*

Histogram equalization is a common technique for enhancing the appearance of images. Suppose we have an image which is predominantly dark. Then its histogram would be skewed towards the lower end of the grey scale and all the image detail is compressed into the dark end of the histogram. If we could 'stretch out' the grey levels at the dark end to produce a more uniformly distributed histogram then the image would become much clearer.

Histogram equalization involves finding a grey scale transformation function that creates an output image with a uniform histogram (shown in fig. 2)

Assume our grey levels are continuous

and have been normalized to lie between 0 and 1

We must find a transformation T that maps grey values r in the input image F to grey values s = T(r) in the transformed image F.

It is assumed that

- T is single valued and monotonically increasing, and
- $0 \leq T(r) \leq 1$ for $0 \leq r \leq 1$.

Fig. 2.1.a. Original Image

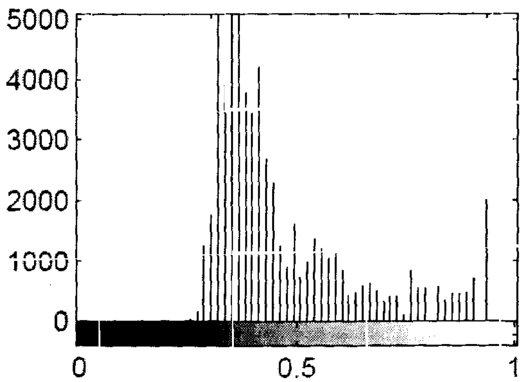

Fig. 2.1.b.Histogram

Fig. 2.2.a. Equalized Image

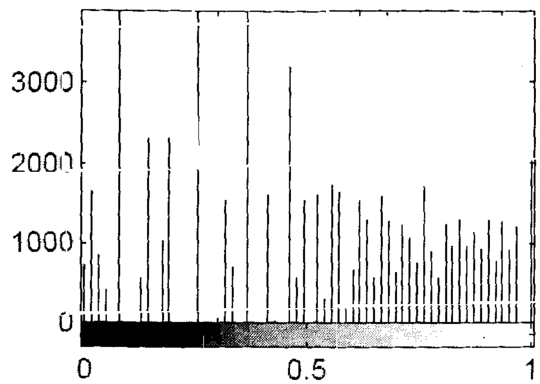

Fig. 2.2.b. Equalized Histogram.

Both images are quantized to 64 grey levels. The inverse transformation from s to r is given by $r = T^{-1}(s)$.

If one takes the histogram for the input image and normalizes it so that the area under the histogram is 1, we have a probability distribution for grey levels in the input image $P_r(r)$.

From probability theory it turns out that

$$P_s(s) = P_r(r)\frac{d_r}{d_w} \qquad \text{(Eq.2.1)}$$

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

Consider the transformation

$$s = T(r) = \int_0^r P_r(w)\, d_w \qquad \text{(Eq.2.2)}$$

This is the cumulative distribution function of r. Using this definition of T we see that the derivative of s with respect to r is

$$\frac{d_s}{d_r} = P_r(r) \qquad \text{(Eq.2.3)}$$

Substituting this back into the expression for Ps, we get

$$P_s(s) = P_r(r)\frac{1}{P_r(r)} = 1 \qquad \text{(Eq.2.4)}$$

for all s; where $0 \le s \le 1$. Thus, $P_s(s)$ is now a uniform distribution function, which is what we want.

2.1.3. *Discrete Formulation*

We first need to determine the probability distribution of grey levels in the input image.

$$\text{Now, } P_r(r_k) = \frac{n_k}{N} \qquad \text{(Eq.2.5)}$$

where $0 \le r_k \le 1$, k is a grey level, n_k is the number of pixels having grey level k, and N is the total number of pixels in the image. Thus the plot of $P_r(r_k)$ is a normalized plot of the histogram.

The transformation now becomes:

$$s_k = T(r_k) = \sum_{i=0}^{k} \frac{n_i}{N}$$

$$= \sum_{i=0}^{k} P_r(r_i) \qquad \text{(Eq.2.6)}$$

The values of s_k will have to be scaled up by 255 and rounded to the nearest integer so that the output values of this transformation will range from 0 to 255. Thus the discretization and rounding of s_k to the nearest integer will mean that the transformed image will not have a perfectly uniform histogram.

2.2. *Frequency domain methods :*

Image enhancement in the frequency domain is straightforward. We simply compute the Fourier transform of the image to be enhanced, multiply the result by a filter (rather than convolve in the spatial domain), and take the inverse transform to produce the enhanced image.

The idea of blurring an image by reducing its high frequency components or sharpening an image by increasing the magnitude of its high frequency components is intuitively easy to understand. However, computationally, it is often more efficient to implement these operations as convolutions by small spatial filters in the spatial domain. Understanding frequency domain concepts is important, and leads to enhancement techniques that might not have been thought of by restricting attention to the spatial domain.

Any periodic function can be represented as the sum of sines and cosines of different frequencies, multiplied by a different coefficient. The sum is called Fourier series. Functions that are not periodic but whose area under the curve is finite can be represented as the integral of sines and cosines multiplied by a weight function known as Fourier transform.

Function represented by Fourier transform can be completely reconstructed by an inverse transform with no loss of information, allows working in Fourier domain and return to the original domain without any loss of information.

3. *Geometric Transformations*

In this section we consider image transformations such as rotation, scaling and distortion of images. Such transformations are frequently used as pre-processing steps in applications such as document understanding, where the scanned image may be mis-aligned.

The number of possible geometric transformations that can be applied to an image is essentially limitless. The possibility ranges from simple transformations to more complex ones. An example of geometric transformations is the RST (rotation, scaling and translation) transform described by the following equation.

$$\begin{pmatrix} u \\ v \end{pmatrix} = S\begin{pmatrix} \cos R & -\sin R \\ \sin R & \cos R \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} T_x \\ T_y \end{pmatrix} \quad \text{(Eq.2.7)}$$

Alternatively, an example of more complex geometric transformations is the bilinear transform described by the following equation:

$$\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} a & c \\ b & d \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} e \\ f \end{pmatrix}xy + \begin{pmatrix} g \\ h \end{pmatrix} \quad \text{(Eq.2.8)}$$

Due to the vast number of possible geometric transforms applied to the image, it is impossible to model each of them individually. There are some approaches that can be used to solve this problem. One approach is to use simpler transformation models, for example RST or affine transform, to approximate the underlying complex, global geometric transform[8]. The approach is based on the assumption that a complex geometric transformation applied on a global scale can be approximated by a simpler transformation model applied on a more local scale. Another possible approach is to use orthogonal polynomials to do the approximation10. In this paper, we use local RST transform to approximate the global underlying transform.

There are two basic steps in geometric transformations:

1. A spatial transformation of the physical rearrangement of pixels in the image,

2. A grey level interpolation, which assigns grey levels to the transformed image

Apart from geometrical transformations some preliminary grey level adjustments may be indicated, to take into account imperfections in the acquisition system. This can be done pixel by pixel, calibrating with the output of an image with constant brightness. Frequently space-invariant grey value transformations are also done for contrast stretching, range compression, etc. The critical distribution is the relative frequency of each greyvalue, the*greyvalue histogram*.

Grey values can also be modified such that their histogram has any desired shape, e.g. flat (every grey value has the same probability). All examples assume *point processing*, viz.

each output pixel is the function of one input pixel; usually, the transformation is implemented with a look-up table.

Physiological experiments have shown that very small changes in luminance are recognized by the human visual system in regions of continuous grey value, and not at all seen in regions of some discontinuities. Therefore, a design goal for image enhancement often is to smooth images in more uniform regions, but to preserve edges. On the other hand, it has also been shown that somehow degraded images with enhancement of certain features, *e.g.* edges, can simplify image interpretation both for a human observer and for machine recognition. A second design goal, therefore, is image sharpening. All these operations need *neighborhood processing*, viz. the output pixel is a function of some neighborhood of the input pixels.

These operations could be performed using linear operations in either the frequency or the spatial domain. We could, *e.g.* design, in the frequency domain, one-dimensional low or high pass filters, and transform them according to McClellan's algorithm to the two-dimensional case.

Here is a trick that can speed up operations substantially, and serves as an example for both point and neighborhood processing in a binary image: we number the pixels in a 3×3 neighborhood like:

5	6	7
4	8	0

and denote the binary values (0,1) by b_i (i = 0,8); we then concatenate the bits into a 9-bit word, like $b_8b_7b_6b_5b_4b_3b_2b_1b_0$. This leaves us with a 9-bit grey value for each pixel, hence a new image (an 8-bit image with b_8 taken from the original binary image will also do). The new image corresponds to the result of a convolution of the binary image, with a 3×3 matrix containing as coefficients the powers of two. This *neighbor image* can then be passed through a look-up table to perform erosions, dilations, noise cleaning, skeletonization, etc.

Apart from point and neighborhood processing, there are also *global processing techniques*, *i.e.* methods where every pixel depends on all pixels of the whole image. Histogram methods are usually global, but they can also be used in a neighborhood.

4. **Conclusion**

The material presented in this paper is representative of image processing techniques commonly used in practice for image enhancement. This area of image processing is a dynamic field, and new techniques and applications are reported routinely in professional literature and in new product announcements. For this reason, the topics included in this paper are selected for their value as fundamental material that would serve as a foundation for understanding the state of the art in enhancement techniques, as well as for further study in this field. In addition to enhancement, this paper served the purpose of introducing a number of concepts.

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