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Gradient Histrogram Preservation for Texture Enhanced Image Denoising

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ABSTRACT

General framework based on histogram equalization for image contrast enhancement is discussed. Inthis framework, contrast enhancement is posed as an optimization problem that minimizes a cost function.Histogram equalization is an effective technique for contrast enhancement. However, conventional histogram

equalization (HE) usually results in excessive contrast enhancement, which in turn gives the processed image anunnatural look and creates visual artifacts. By introducing specifically designed penalty terms, the level of

contrast enhancement can be adjusted; noise robustness, white/black stretching and mean-brightnesspreservation may easily be incorporated into the optimization.

KEYWORDS : Histogram equalization, histogram modification, image/video quality enhancement.

INTRODUCTION

Contrast enhancement plays a crucial role in image processing applications, such as digitalphotography, medical image analysis, remote sensing, LCD display processing, and scientificvisualization. Image enhancement is a technique which reduces image noise, removeartifacts, and preserve details. Its purpose is to amplify certain image features for analysis,diagnosis and display.

Contrast enhancement increases the total contrast of an image by making light colors lighterand dark colors darker at the same time. It does this by setting all color components below aspecified lower bound to zero, and all color components above a specified upper bound to themaximum intensity (that is, 255). Color components between the upper and lower bounds areset to a linear ramp of values between 0 and 255. Because the upper bound must be greaterthan the lower bound, the lower bound must be between 0 and 254, and the upper bound mustbe between 1 and 255. Some users describe the enhanced image that if a curtain of fog hasbeen removed from the image [1].

There are several reasons for an image/video to have poor contrast:

- the poor quality of the used imaging device,
- lack of expertise of the operator, and
- The adverse external conditions at the time of acquisition.

These effects result in under-utilization of the offered dynamic range. As a result, suchimages and videos may not reveal all the details in the captured scene, and may have awashed-out and unnatural look.

2. IMAGE ENHANCEMENT

Image enhancement processed consist of a collection of techniques that seek to improve the visual appearance of an image or to convert the image to a form better suited for analysis by a human or machine[2] . Enhancement of an image can be implemented by using different operations of brightness increment, sharpening, blurring or noise removal. Unfortunately, there is no general theory for determining what 'good' image enhancement, when it comes to human perception. If it looks good, it is good! While categorizing Image Enhancement operations can be divided in two categories:

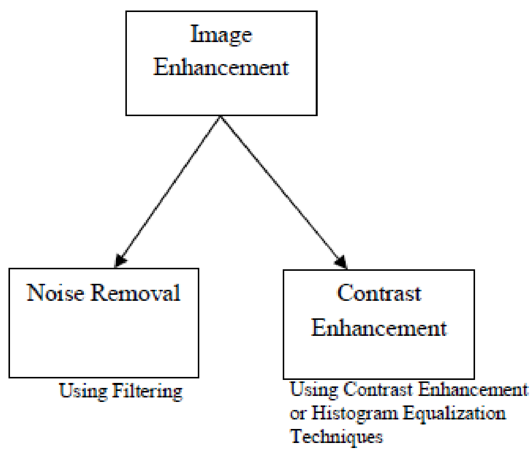

Figure 1 : Operations of Image Enhancement

As shown in Fig. 1.1, image enhancement can be implemented by Noise removal or Contrast Enhancement [3]. Noise Removal is an operation to remove unwanted details from an image. This detail gets attached to an image while capturing or acquisition process. Noise may be due to environment particles, capturing device inability, lack of experience of machine computer operator or some other reason. Noise removal helps an image processing system to extract necessary information only.

Other operation of Image Enhancement is Contrast Improvement. This process is used to make the image brighter, visual and detail worth full. Contrast Enhancement is the major area of this study and represents various methodologies being used for this process.

2.1 TECHNIQUES OF CONTRAST ENHANCEMENT

These techniques can be broadly categorized into two groups:

- direct methods and,
- Indirect methods.

2.1.1 Direct method

In direct method of contrast enhancement, a contrast measure is first defined, which is thenmodified by a mapping function to generate the pixel value of the enhanced image. Variousmapping functions such as the square root function, the exponential function, etc., have beenintroduced for the contrast measure modification. However, these functions do not producesatisfactory contrast enhancement results and are usually sensitive to noise and digitizationeffects [4]. In addition, they are computationally complex from the point of view ofimplementation. The polynomial function is ready to implement on digital computers andprovides very satisfactory contrast enhancement.

2.1.2 Indirect method

Indirect methods, on the other hand, improve the contrast through exploiting the underutilizedregions of the dynamic range without defining a specific contrast term. Most methodsin the literature fall into the second group [4]. Indirect methods can further be divided intoseveral subgroups:

- techniques that decompose an image into high and low frequency signals formanipulation, e.g., homomorphic filtering,
- Histogram modification techniques, and
- Transform-based techniques.

Out of these three subgroups, the second subgroup received the most attention due to itsstraightforward and intuitive implementation qualities.

3. HISTOGRAM EQUALIZATION

Contrast enhancement techniques in the second subgroup modify the image through somepixel mapping such that the histogram of the processed image is more spread than that of theoriginal image. Techniques in this subgroup either enhance the contrast globally or locally. Ifa single mapping derived from the image is used then it is a global method; if theneighborhood of each pixel is used to obtain a local mapping function then it is a localmethod. Using a single global mapping cannot (specifically) enhance the local contrast [5],[6]. One of the most popular global contrast enhancement techniques is histogramequalization (HE).

The histogram in the context of image processing is the operation by which the occurrence of each intensity value in the image is shown. Normally, the histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8- bit grayscale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels amongst those grayscale values [7]. Histogram equalization is the technique by which the dynamic range of the histogram of an image is increased. HE assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities. It improves contrast and the goal of HE is to obtain a uniform histogram. This technique can be used on a whole image or just on a part of an image. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. 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. The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed.

Advantage: A key advantage of the method is that it is a fairlystraightforward technique and an invertible operator. So in theory, if thehistogram equalization function is known, then the original histogram can be recovered.

Disadvantage: A disadvantage of the method is that it is indiscriminate. Itmay increase the contrast of background noise, while decreasing the usablesignal.

Histogram equalization is a specific case of the more general class of histogram remappingmethods. These methods seek to adjust the image to make it easier to analyze or improvevisual quality. The above describes histogram equalization on a grey-scale image. However itcan also be used on color images by applying the same method separately to the Red, Greenand Blue components of the RGB color values of the image. Still, it should be noted thatapplying the same method on the Red, Green, and Blue components of an RGB image mayyield dramatic changes in the image's color balance since the relative distributions of thecolor channels change as a result of applying the algorithm. However, if the image is firstconverted to another color space, Lab color space, or HSL/HSV color space in particular,then the algorithm can be applied to the luminance or value channel without resulting inchanges to the hue and saturation of the image [3]

The histogram is a discrete function

$h(r=k) = nk$,

Where nk is the number of pixels in the image having gray level k

It is a common practice to normalize a histogram by dividing each of its values by the total number of pixels in the image (n)

$p(r=k) = nk/n$, $k=0, 1, \ldots, L-1$

Where $p(r=k)$ is an estimate of the probability of occurrence of gray level k [8].

Following graph shows the histogram equalization for 2D image:

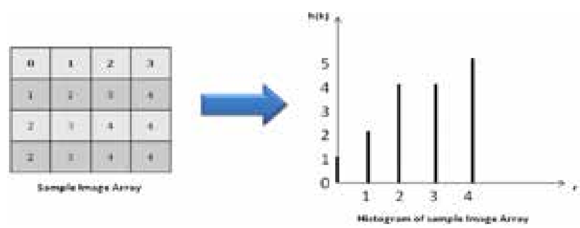

Figure 2 Sample Histogram for a 2D Image Array

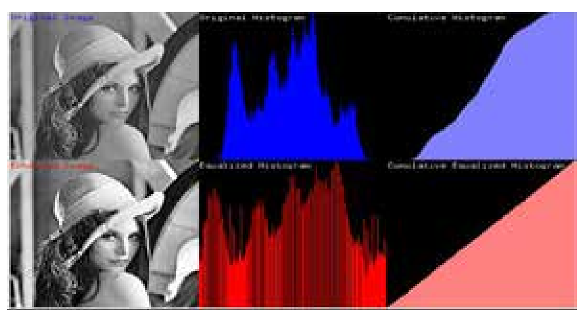

Figure 3 : Histogram of Image

Figure-4.Original image. &Noisy image with mean = 0, S.D*=20.

Figure-5. Noisy image with mean = 0, S.D*=30. &Denoised image.

Algorithm Used :

1. Initialize $k = 0, x^{(k)} = y$
2. Iterate on $k = 0,1,2,\ldots,J$
3. Update g:

$$g = F(\nabla x)$$

4. Update x:

$$x^{(k+1)/2} = x^{(k)} + \delta\left(\frac{1}{2\sigma^2}(y - x^{(k)}) + \mu\nabla^T(g - \nabla x^{(k)})\right)$$

5. Update the coding coefficients of each patch:

$$\alpha_i^{(k+1/2)} = D^T R_i x^{(k+1/2)}$$

6. Update the nonlocal mean of coding vector:

$$\beta_i = \sum_q w_i^q \alpha_i^q$$

7. Update α:

$$\alpha_i^{(k+1)} = S_{\lambda/d}\left(\alpha_i^{(k+1/2)} - \beta_i\right) + \beta_i$$

8. Update x:

$$x^{(k+1)} = D \circ \alpha^{(k+1)}$$

9. $k \longleftarrow k + 1$
10. $x = x^{(k)} + \delta\left(\mu\nabla^T(g - \nabla x^{(k)})\right)$

4. EXPERIMENTAL RESULTS

To verify the performance of the proposed Gradient Histogram Preservation (GHP) based image denoising method, we apply it to ten natural images with various texture structures, whose scenes are shown in Figure-6. All the test images are gray-scale images with gray level ranging from 0 to 255. We first discuss the parameter setting in our GHP algorithm.

Finally, experiments are conducted to validate its performance in comparison with the state-of-the-art denoising algorithms.

5.CONCLUSIONS

In this paper, we presented a gradient histogrampreservation (GHP) model for texture-enhanced imagednoising. An efficient iterative histogram specificationalgorithm was developed toimplement the GHP model.GHP achieves promising results in enhancing the texturestructure while removing random noise. The experimentalresults demonstrated the effectiveness of GHP in textureenhanced image denoising. GHP leads to PSNRmeasuresto the state-of-the-art denoising method. However, it leads to more naturaland visually pleasantdenoising results by better preserving the image textureareas. Most of the state-of-the-art denoising algorithms arebased on the local sparsity and nonlocal self-similaritypriors of natural images. Limitations of GHP is that itcannot be directly applied to non-additive noise removal.The computational time is approximately 40 min.

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