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Histogram Domain Adaptive Power Law Applications in Image Enhancement Technique

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***Abstract*— This paper presents a histogram domain adaptive power law application image enhancement technique. In this technique , adaptative power law transformation is applied on the histogram equalized value of an input image. Adaptation is carried out directly on the original image pixel and manipulation is done indirectly on the histogram equalized pixel value. This can control the over contrast or brightness condition caused by histogram process. Normally local adaptation techniques are time consuming and computational time is local block size dependent. In this technique local adaptation is carried out with the help of a local threshold value whose computational time complexity is independent from local block size. Hence this new enhancement technique is also local block size independent computational time complexity. This technique can be applied both on gray and colour images. In the case of colour image, transformation is applied on R-G-B space separately with a single histogram domain of grey-scale image of colour image. From the experimental result, we observe that this technique outperforms other related techniques.**

***Keywords*— Image histogram, Adaptive, power law, local contrast, Global contrast, Edge sharpening, Artefact, Integral average image.**

I. INTRODUCTION

Image enhancement is a process of transforming an image to a new image with a suitable transforming function. Contrast and edge enhancement are important parts of image enhancement. In medical imaging, computer vision and image recognition process, contrast and edge enhancement are very important. When diagnosis of many diseases such as chest radiography and mammography [1-2] visual examination is essential. Normally medical images are inherently low contrast due to the small differences in the X-Ray attenuation coefficients. But how to enhance the contrast and edge of an image is a vital factor in image enhancement process.

Power Law Transformations (PLT) [3], Histogram Equalization(HE) [3-5] and Adaptive Contrast Enhancement (ACE) [6-8] are contrast enhancement methods for poor intensity distribution images. These techniques can enhance only the global contrast but fail for local contrast enhancement. Normally, most of the enhancement technique are dedicated to a certain purpose say contrast enhancement technique fails in edge enhancement while edge enhancement technique fails in contrast enhancement. Local technique can enhance the local contrast which can make the local edge enhancement. But local techniques are time consuming depending the computational time on local block size. Local mean is commonly used in local technique for local contrast adaptation. Local mean calculation is time consuming. Integral sum image is a way of calculating local mean without depending on the local block size. However local mean cannot control the levels of adaptation since the local mean is a constant within the block. Local thresholding technique can adjust the local adaptation varying the threshold value depending on the desired levels of adaptation with parameters. T.R Singh *et al* [9] propose a local thresholding technique which uses integral image [10] to calculate the local mean so that the computational time is free from local block size. Singh *et al* [11-12] propose Adaptive Power law Transformations(APLT) for image enhancement through contrast stretching as well as edge sharpening. These techniques fail in local contrast for some image type. Histogram processing technique stretch global contrast. Sometimes it produces over contrast for low contrast images. If APLT is applied on histogram domain of the input image, it can control the over contrast caused by histogram technique resulting a well-balanced contrast image. Based on this idea, an image enhancement technique “Histogram Domain Adaptive Power Law Application in Image Enhancement Technique” is proposed.

This paper is organized as follows. Section II describes prerequisite background. Section III describes the Adaptive power technique. Section IV describes proposed technique. Section V describes the experimental result and Section VI gives the conclusions.

II. PREREQUISITE BACKGROUND

A. Integral sum image

An integral sum image $I_s(x, y)$ of an input image *I* is defined as the image in which the intensity at a pixel position (*x,y*) is equal to the sum of the intensities of all the pixels above and to the left of that position in the original image. It can be defined as :

$$I_s(x, y) = \sum_{i=1}^{x} \sum_{j=1}^{y} I(i, j) \tag{1}$$

Integral sum image representation has a problem of storage if the image dimension is very large. This problem can be solved by representing as integral average image.

B. Integral Average Image

The integral average image I_a [10],[12] of an input image *I* is defined as similar to integral sum image but the difference is only the representation value. It can be defined as :

$$I_a(x,y) = \frac{1}{x \times y} \sum_{i=1}^{x} \sum_{j=1}^{y} I(i,j) \quad (2)$$

Since the average value is stored at each location, there is no storage representation problem. Once integral sum/average image is formed , local sum within a local block of size $w \times w$ can be calculated easily without depending the computational time on the local block size.

C. Local sum and mean calculation

Local sum $s(x,y)$ at (x,y) within a block window of size $w \times w$ can be calculated from the integral average image I_a with the following equation as:

$$s(x,y) = [I_a(x+d,y+d)\times(x+d)\times(y+d) + I_a(x-d-1,y-d-1\times(x-d-1) \times(y-d-1)] - I_a(x-d-1,y+d)\times(y-d-1)] - I_a(x-d-1,y+d)\times(x-d-1) \times(y+d) + I_a(x+d,y-d-1)\times(x+d)\times(y-d-1)] \quad (3)$$

where $d = \frac{w-1}{2}$

From the local sum $s(x,y)$, local mean $m(x,y)$ can be determined as:

$$m(x,y) = \frac{s(x,y)}{w \times w} \quad (4)$$

D. Local thresholding

Local threshold value T of a grey-scale image is defined within a local block of size $w \times w$ as :

$$b(x,y) = \begin{cases} 0 & if \quad I(x,y) \le T \\ 1 & otherwise \end{cases} \quad (5)$$

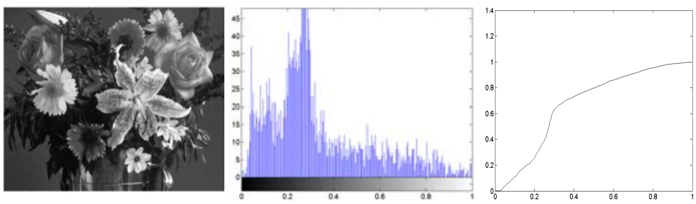
where $b(x,y) \in \{0,1\}$ and $I(x, y) \in [0,1]$ are the intensity of pixels at location (x, y) of the binary image b and input image I respectively. In local technique, a threshold is calculated for each pixel, based on some local statistics of the neighborhood pixels within the block. Hence local techniques are time consuming to process the local statistics like local mean and standard deviation. So as to minimize the computational time of local mean calculation, Singh *et al* [9] propose an efficient way of determining local threshold. They used integral sum image $s(x,y)$ as a prior process to determine the local mean m(x, y). But Integral sum image representation has a problem of large value of sum. To solve this problem, they propose integral average image[12] representation as in equation(2). Local sum s(x, y) and local mean m(x,y) are determined using equations (3) and (4) respectively. This technique of thresholding use only mean while other techniques like Savona's [13] use both mean and standard deviation. Hence technique of Singh et al [9] to determine the local threshold value is used and expressed as:

$$T(x,y) = m(x,y)\left[1 + k_1\left(\frac{\partial(x,y)}{1-\partial(x,y)} - 1\right)\right] \quad (6)$$

where $\partial = I(x,y) - m(x,y)$ is the local mean deviation and $k_1 \in [0,1]$ is a bias which can control the level of adaptation varying threshold value. It controls the area of foreground and background in the binarised image resulting a convenient way of controlling area where contrast to be stretched.

E. Image Histogram

The graphical representation of the total tonal distribution in a digital image is called an image histogram**[3]**. It plots the number of pixels for each tonal value along vertical and tonal range [0,1] from left to right along horizontal as in Fig.1.



(a) Input image (b) Histogram of input image (b) Histogram Equalization

Fig.1 Image Histogram representation

The prot in the image $I \in [0, L-1]$ in normalised form is defined as :

$$H_x(i) = \frac{n_i}{n}, \; 0 \le i < L-1 \quad (7)$$

where *L* being the total number of gray levels in the image, n_i is the total number of tonal value i , n is the total number of pixels in the image, and $H_x(i)$ is the image's histogram for pixel value *i* which is normalized to [0,1].

F. Histogram Equalisation

Cumulative distribution function(CDF) of H_x is define as:

$$h_x(i) = \sum_{j=0}^{i} H_x(j) \quad (8)$$

The image's accumulated normalized histogram and its representation is shown in Fig. 1. We can create a transformation of the form $v = T(r)$ to produce a new image I_h, such that its CDF will be linearized across the value range, as :

$$v = T(r) = floor\ ((L-1)h_x(r)) \tag{9}$$

This means that the T maps the levels of input pixel $r \in [0,1]$ into the range of $v \in [0,1]$ as the pixels of output image I_h. This mapping method can be used as contrast adjusting technique.

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. 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. This method is applied only on grey-scale image. However it can also be used on color images by applying the same method separately to the Red, Green and Blue components. But, application of this method on the Red, Green, and Blue components may yield dramatic changes in the image's colour balance. However, if the image is first converted to another colour space, like HSL/HSV colour space or take its grey-scale image then the method can be applied to the single histogram equalisation value of the luminance or grey-scale image for each channel of R-G-B. Normally histogram processing is over contrast in some image types.

III. ADAPTIVE POWER LAW TECHNIQUES

Standard power law transformation(PLT) function is defined as :

$$v = cr^{\gamma} \tag{10}$$

where c and γ are two constants while r is the input pixel value. This two constants can control brightness and global contrast. It cannot control the local contrast and edge sharpness. If it is applied on local block, it can control the local contrast and edge sharpness.

A. Adaptive Power Law Transformation using Local Mean

TR Singh *et al* [11] proposed adaptive power law transformation(APLT) function using local mean for adaptation in image enhancement technique and express as :

$$I'(x,y) = c(1+k\partial)I(x,y)^{\gamma(1-k\partial)} \tag{11}$$

where $\{I'(x,y), I(x,y)\} \in [0,1]$ are the output image and input image. c, γ and k are constants which control the brightness, contrast and edge sharpness/smoothness of I'.

$$\partial = I(x,y) - m(x,y) \tag{12}$$

where $m(x,y)$ is the local mean of the input image within a window of size $w \times w$ with $I(x,y)$ as centre at (x,y) of the window.

If k=0, then it is equivalent to the PLT and if $k \neq 0$, then the three parameters take different roles of varying different levels of enhancement of the output image unlike PLT. There will be three controls depending on the different parameters such as brightness, contrast and edge sharpness/ smoothness of the output image. Calculation of local mean is time consuming and time complexity is local block size dependent.

B. Adaptive Power Law Transformations using Local Threshold value

In APLT, adaptation is carried out with local mean and local mean determination is time consuming. Not only time consuming, adaptation level cannot be varied trough local mean. Hence T.R Singh *et al* [12] proposed Threshold based Adaptive Power law Application(TAPLA) where adaptation is carried out with a local threshold value T [9] which is determined with the technique as in equation(6). Since this thresholding technique is free from local block size dependent time complexity, TAPLA is s also free from this. This technique similar to APLT but the difference is that the local mean $m(x,y)$ is replaced by a local threshold value $T(x,y)$ as in following expression:

$$I'(x,y) = c(1+k\partial)I(x,y)^{\gamma(1-k\partial)} \tag{13}$$

$$\partial = I(x,y) - T(x,y) \tag{14}$$

In this technique a thresholding technique is used to vary the adaptation level, and adaptation level can be adjusted with a bias control parameter k_I. Its function is similar to APLT but it can adjust the adaptation level with k_I.

IV. PROPOSED TECHNIQUE

This new technique of image enhancement is to apply adaptive power law transformation on histogram domain of an input image *I*. In APLT and TAPLA, the transformation function is applied on the direct original pixel of the image. In normal histogram processing technique, global contrast of an image can be increased but over contrast is occurred in some certain image type. In this new technique it can be controlled by the transforming function. The transforming function is similar to TAPLA. Hence this technique also has the same activity of TAPLA but the difference is only the input value. Since the input value is the histogram matched of the original pixel value, the output value is different from TAPLA and this result is improved from TAPLA.

In the case of colour image there will be only one histogram domain H_g for all R-G-B channels and transforming function is applied based on the single histogram domain. But the adaptation is carried out channel wise separately to the original image. The single histogram domain is determined from the grey-scale image I_g of the input colour image. The transformation functions can be expressed as

$$O(x,y) = c(1+k\rho)h^{\gamma(1-k\rho)} \quad (15)$$

$$h = H_g(r) \quad (16)$$

$$r = I(x,y) \quad (17)$$

$$\rho = r - T(x,y) \quad (18)$$

where h is the histogram matched value of r, $T(x,y)$ is the local threshold value of original pixels within a window of size $w \times w$ defined in equation(6). c, k and γ are the constant parameter like in TAPLA.

Algorithm

1. Take the input image I.
2. Take grey-scale image I_g of the input image I. If the image is of grey-scale, skip this step and $I_g = I$.
3. Generate the histogram equalized image H_g of the grey-scale image I_g.
4. Repeat transformation function application on histogram domain until last the pixel.
   i. $r = I(x,y)$: *original pixel value at* (x,y).
   ii. $h = H_g(r)$: *histogram matched value of* r.
   iii. $\rho = r - T(x,y)$:*Calculate the local threshold value T(x,y) and determine* ρ.
   iv. $O(x,y) = c(1+k\rho)h^{\gamma(1-k\rho)}$: application of *adaptive power law transformation on histogram domain to produce output image O.*
5. Stop.

Transformation function is equivalent to TAPLA and hence it has the same activity of TAPLA. Like TAPLA if k=0 it is same as PLT and if $k \neq 0$ there are various contrast adjustment levels depending on the value of ∂ with k as a positive constant. Those pixel whose values are below the threshold $T(x,y)$, *i.e.* $\rho < 0$ will give higher value of $\gamma(1-k\rho)$ and lower value of $c(1+k\rho)$ resulting lower transformed value of $O(x,y)$. Those pixels whose values are greater than the threshold $T(x,y)$, *i.e.* $\rho > 0$ will give lower value of $\gamma(1-k\rho)$ and higher value of $c(1+k\rho)$ resulting higher transformed value of $O(x,y)$. If k is negative constant, the result will be opposite resulting a smooth image output. Depending on the values of γ, there will be various levels of enhancement unlike APLT and TAPLA keeping the others parameters constant. As ρ depends on $T(x,y)$ and $T(x,y)$ depends on k_1, k_1 also take a major role in this technique. Thus in this transformation technique, there may not be over all increase or decrease at the output values. The value of ρ varies the level of contrast adjustment with the value of γ.

Fig. 2 shows the graphical representation of difference in nature of signals between HE and HDAPLA as in Fig. 3 which shows the result of histogram equalised image and HDAPLA with their histogram. Fig. 3(b) shows the histogram equalised image and it is found from the result that it is over brighten and its histogram is closed towards right side. Fig. 3(c) shows the result of HDAPLA. In this result the over brighten image caused by histogram equalised image is controlled by HDAPLA. Figs 4 to 6 show the comparisons of results different related techniques with HDAPLA.

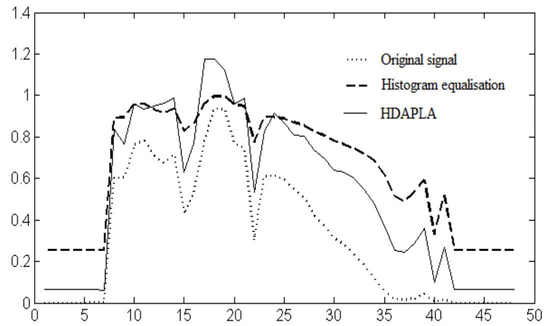
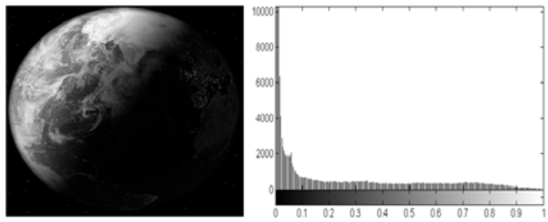
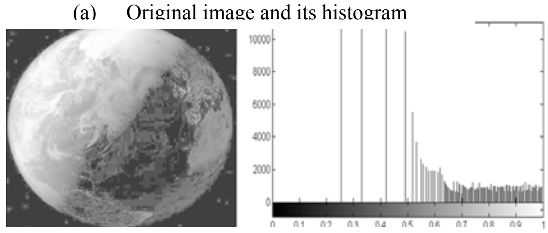


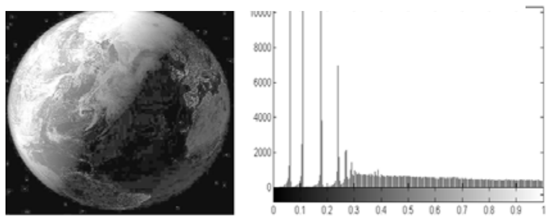
Fig. 2 Different signals of original image, histogram equalized image and result image of HDAPLA.



(a) Original image and its histogram



(b) Histogram equalized image and its histogram



(c) Result of HDAPLA and its histogram

Fig.3 Histogram of different images

V. Experimental Result

This proposed enhancement technique is tested on many categories of images and compare with other spatial domain techniques like Histogram equalization, and TAPLA qualitatively as well as quantitatively. Qualitative evaluation provides a set of images for visual perception by human beings as in Figs 4 to 6. It is highly subjective and it is not convenient to quantify the enhancement for analysis. A quantitative measure is also needed in case of parameter based algorithms to identify the optimum enhancement point. This new technique associates contrast stretching, brightness as well as edge sharpness/smoothness and hence the measure of enhancement by entropy (*EME*) [23,24,25] for evaluating our contrast enhancement results and Tenengrad measure (*TEN*) [26, 27, 28] is employed for evaluating edge information for sharpness/smoothness.

A. Measure of Enhancement by Entropy

Measure of Enhancement by Entropy (*EME*) is based on entropy of contrast established on the foundation of the Michelson contrast measure [23] and uses elements of human visual perception. It is expressed as:

$$EME = \frac{1}{p \times q} \sum_{x=1}^{p} \sum_{y=1}^{q} \frac{I_m(x,y)}{I_n(x,y)+e} \log\left(1 + \frac{I_m(x,y)}{I_n(x,y)+e}\right) \quad (19)$$

Where $p \times q$ is the total number of non-overlapping blocks of size $b \times b$ in the image $I_{m \times n}$ such that $p = \frac{m}{b}$ and $q = \frac{n}{b}$. $I_m(x,y)$ and $I_n(x,y)$ are the maximum and minimum grey level value of pixels within the block (x,y), e is a very small constant added to the denominator to avoid division by zero. Higher value of *EME* denotes a higher contrast and information clarity in the image. Some of the tested images are applied *EME* for comparison with others and *EME* comparision is shown in Table I and Fig 7.

B. Tenengrad Measure

Tenengrad measure (*TEN*)[26,27,28] is based on gradient magnitude maximization. Tenengrad value of an image f is calculated from the gradient $\nabla f(x, y)$ at each pixel location (x,y), where the partial derivatives are obtained by a high pass filter like the Sobel operator, with the convolution kernels i_x and i_y. The gradient magnitude is given as

$$S(x,y) = \sqrt{(i_x \times f(x,y))^2 + (i_y \times f(x,y))^2} \quad (20)$$

Tenengrad criteria is then calculated as

$$TEN = \sum_x \sum_y S(x,y)^2 \quad (21)$$

The image quality in terms of sharpness and edge information is usually considered higher if the *TEN* value is larger. In smoothening case *TEN* value is low for more smooth image as compare with the original image. Hence *TEN* value is depend on the evaluation purpose. Table II and Fig.8 show the *TEN* comparison with others based on some of the tested images.

Normally local techniques are local window size dependent and its computational complexity is $O(n^2 \times w^2)$ for an image of size $n \times n$ with local window size $w \times w$. But here in this proposed technique it is local window size independent as a result of using integral average image to determine local mean $m(x,y)$ like TAPLA. Hence its computational time complexity is $O(n^2)$ which is very closed to global techniques.

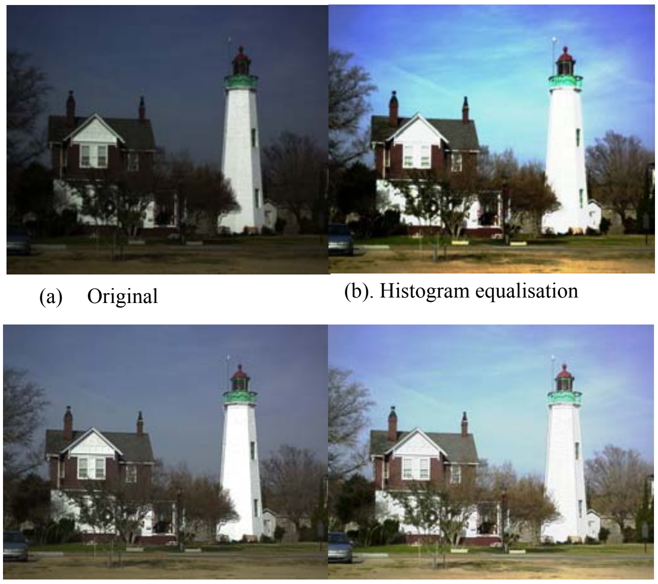
VI. CONCLUSION

This paper presents a histogram domain adaptive power law application technique of image enhancement. This new technique can control the over brightness of contrast of histogram equalization technique with parameters. It is similar to TAPLA but the difference is only the input value. Hence it is also has the capability of controlling an image brightness, global contrast and local edge sharpness.

(a). Original (b). Histogram equalization

(c). TAPLA at γ=0.65, C=2, k=2, k_1=0.06 (d). HDAPLA at γ=0.75, C=1.15, k=2, k_1=0.06

Fig 4 Retinex image23 for visual comparison with other techniques.



(a) Original (b). Histogram equalisation

(c). TAPLA at γ=0.65, C=1, k=2, k_1=0.06 (d). HDAPLA at γ=0.55, C=0.85, k=2, k_1=0.06

Fig 5 Retinex image22 for visual comparison with other techniques.

(a). Original image (576×886) (b). Histogram Equalization

(c). TAPLA at γ=0.7, C=1, k=4, $k1$=0.0.6 (d). HDAPLA at γ=0.7, C=0.8, k=4, $k1$=0.0.6

Fig 6 Visual comparison of results of different methods on retinex image20

TABLE I

EME Comparison of HDAPLA with other methods based on Figs given in the list.

Fig. Nos.	*EME*		
	Original	TAPLA	HDAPLA
Fig: 8	2	793	917
Fig: 5	4	497	584
Fig: 4	162	1505	2562

TABLE I I

TEN Comparison of HDAPLA with other methods based on Figs given in the list.

Fig. Nos.	*TEN*		
	Original	TAPLA	HDAPLA
Fig: 8	74782	309820	322330
Fig: 5	10117	113190	129390
Fig: 4	157160	706650	701870

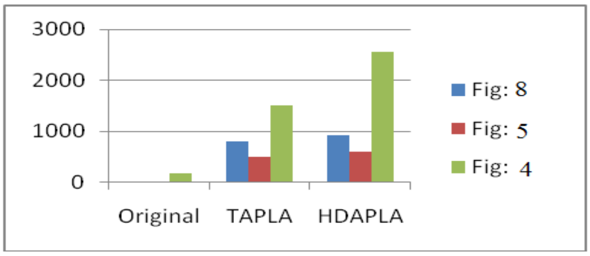


Fig. 7 *EME* comparison chart for Table I

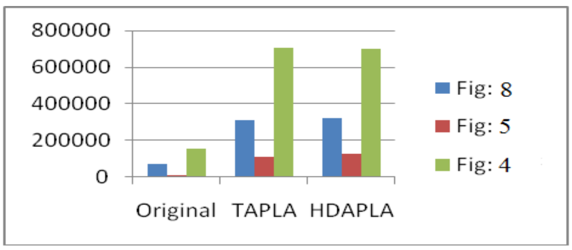


Fig. 8 *TEN* comparison chart for Table II

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