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Image Contrast Enhancement Technique Based on New Definition of Probability Mass Function

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ABSTRACT

The purpose of contrast enhancement is to disclose the hidden details in the image. In this paper, a contrast enhancement method based on image spatial variations is used to identify a new definition of probability mass function. Then, the amount of contrast that should be inserted to each pixel is specified based on the new definition in each image region. Extensive simulation results prove that the proposed method delivers fascinating visual results compared to other known methods either in terms of image quality or details preservation.

Index Terms: Contrast enhancement, image details, probability mass function

1. INTRODUCTION

Contrast enhancement plays a vital role in low level image processing tasks. It is used to reveal hidden details in the captured scene, and to produce informative images of high quality. Contrast enhancement increases the intensity difference between the objects and the background in the image to reveal the hidden data [1-4], also to enhance the human-machine perception. Accordingly, it is demanded for many applications, such as digital photography, biomedical image analysis, remote sensing, LCD display processing, consumer devices, autonomous navigation, and remote sensing [5]. The literature review identified a number of image enhancement methods to produce a pleased image outlook. The most popular technique is histogram equalization (HE), which is commonly used, and whose main advantage is its simplicity and ability to deliver a relatively better performance for almost all image types.

The principle of HE is based on remapping the gray levels of the image due to the implementation of probability mass function of the input gray levels. It flattens and broadens the dynamic range of the image histogram in order to enclose more image details [2]. A global HE [6-8] is one of the techniques of the HE family. Nevertheless, this approach has several major drawbacks. Firstly, histogram equalization produces a flat histogram with a mean value in the middle of the dynamic range, regardless of the mean of the input image, thus significantly altering the image outlook at the cost of enhancing the image contrast. Secondly, large bins cannot be redistributed to generate a flat histogram. Thirdly, the difference between the large and small bins causes over-enhancement and saturation artifacts [9].

Finally, the local image details are not engaged in the enhancement process. A local histogram equalization (LHE) method is proposed for utilizing the local image details, in which the intensity of the pixel at the center of the sliding window is changed according to a local intensity remapping in the sliding window. Although the LHE achieves great contrast results, it sometimes produces over-enhance images. Moreover, it consumes high computation time, because it proceeds on every pixel in the image. Some extension methods for GHE have been proposed to preserve brightness in consumer electronics, such as brightness preserving bi-histogram equalization (BBHE) [10], dualistic sub-image histogram equalization (DSIHE) [11], minimum mean brightness error bi-histogram equalization (MMBEBHE) [12], brightness preserving dynamic histogram equalization (BPDHE) [13], and others.

These methods segment the histogram of the original image into sub histograms and, afterwards, each sub histogram is equalized independently with GHE. For example, BBHE, DSIHE, and MMBEBHE divide the histogram into two sub-histograms. BBHE and DSIHE divide the original histogram based on the mean and the median value, respectively. MMBEBHE examines all possible partitioning values in the dynamic range. The difference between the mean value of the original image histogram and that of each sub-histogram is calculated for every separating point, which in turn minimizes the difference between the input and output means. Although these methods can preserve image brightness to some extent, it may produce degraded images. Recently, a genetic algorithm of free-parameters has been developed by maximizing the contrast measure based on edge information [14]. Turgay in [4] proposed a new method, in which the pixel values of the input image are modeled using the Gaussian mixture technique. A new algorithm is suggested to increase the difference between the image pixel and its neighboring in [15]. Though these methods improve images of low contrast, they show difficulties in improving images of high contrast.

2. ALGORITHM DESCRIPTION

The most important aspect about image contrast enhancement is the disclosure of the unseen details in the image, particularly a blurred or fogged image. The emerged details enable the experts to make the right decision while analyzing many advance image processing tasks, such as object recognition, image segmentation, image coding, and edge detection. A contrast enhancement method should produce high quality images devoid of any degradation that may destroy the existing details. To this end, the inserted contrast should be distributed in the image so accurately to preserve a pleased image outlook. In this paper, we try to use one property existing in all images to be used as a scale or benchmark for determining the inserted contrast in the different image parts. It is well known that each image consists of different regions such as texture R_t ,edge R_e, black R_b, white R_w regions and every region may have sub-regions each with specific contents. Therefore, each pixel can be manipulated by utilizing the features of its neighboring pixels.

In other words, to disclose the details of a specific part in the image, we should increase the amplitude of each pixel in this part and, at the same time, preserve the image details and outlook. To this end, we should increase the amplitude of each pixel or region with a different contrast value. The amplitude level can be determined on the basis of the number of neighboring pixels, which are similar to the tested pixel, i.e. a pixel located in the edge area will increase with a level not equal to that of a pixel located in a homogeneous area. Since each pixel has a different intensity distance with its neighbors, each has a different number of similar pixels. More specifically, the intensity distance between the pixels in the black d^{R_b} or white region d^{R_w} is smaller than that of other regions. Besides, the distance between the pixels in texture regions d^{R_t} is smaller than that of the edge pixels d^{Re} as the following:

$$(d^{R_b} \bigcup d^{R_w}) < d^{R_t} < d^{R_e} \tag{1}$$

Consequently, pixels in edge and texture regions have different numbers of similar pixels and will, therefore, receive different amounts of contrast. Referring to the previous discussion, the a mount of contrast in different regions is calculated, in this paper, based on a new definition of probability mass function (pmf) defined as:

$$p(x_{ij}) = \frac{m_{ij}}{n} \tag{2}$$

m_{ij} is the number of the pixels that are deviated within an intensity range d from the tested pixel x_{ij}, n is the total number of pixels around the tested pixel. Given a window W in the image of size kxm centered at the pixel x_{ij}. Then, to calculate the number m_{ij} and $p(x_{ij})$ for each pixel y ϵ W, compute the probability P (.) of the Absolute Deviation (AD) with respect to the tested pixel x_{ij} and the constant range d as:

$$AD_{ij} = \left| x_{ij} - y \right| \tag{3}$$

$$P\left(\left| x_{ij} - y \right| \le d\right) = \begin{cases} 1 & | x_{ij} - y | \le d \\ 0 & else \end{cases} \tag{4}$$

$$\begin{gathered} for\ every\ pixel\ \ y\ in\ w, \\ \sum_y P\left(\left| x_{ij} - y \right| \le d\right) = m_{ij} \end{gathered} \tag{5}$$

$$p(x_{ij}) = \frac{m_{ij}}{km-1} \qquad 0 \le m_{ij} \le km-1 \tag{6}$$

Note that, $$L_{\min} \leq \left|x_{ij} - y\right| \leq L_{\max} \tag{7}$$

L_{min} and L_{max} are the minimum and maximum intensity values in the image. It is clear that: (m_{ij}|new pmf definition)≥ (m_{ij}|known pmf definition). The reason is that in the new definition, we actually use the local information included in the neighboring pixels. It should be considered that the different values of AD obtained at texture and edge regions, for example, imply that:

$$m_{ij}^{R_t} > m_{ij}^{R_e} \tag{8}$$

$$p(x_{ij}^{R_t}) > p(x_{ij}^{R_e}) \tag{9}$$

Multiplying 9 by the tested pixels of each region, two different contrast quantities Δ's are obtained even the tested pixels in the two regions are equal $x_{ij}^{R_t} = x_{ij}^{R_t}$, as:

$$x_{ij}^{R_t} p(x_{ij}^{R_t}) \neq x_{ij}^{R_e} p(x_{ij}^{R_e}) \tag{10}$$

Since (m_{ij}|smooth area)>(m_{ij}|edge area), then pixels in smooth area will be enhanced more than the pixels in the edge area. The inserted amount of contrast can be increased after N iterations Δ_{ij}^{N} for each pixel as:

$$\Delta_{ij}^{N} = \gamma \sum_{n=1}^{N} x_{ij}^{n} p(x_{ij}^{n}) = \gamma E(X_{ij}) \tag{11}$$

$$X_{ij} = \{x_{ij}^{1}, x_{ij}^{2}, \ldots\ldots, x_{ij}^{N}\} \tag{12}$$

$$P_{ij} = \{p_{ij}^{1}, p_{ij}^{2}, \ldots\ldots, p_{ij}^{N}\} \tag{13}$$

$$p_{ij}^{n} = p(x_{ij}^{n}),\ \gamma \geq 0 \tag{14}$$

γ is a contrast gain used to specify the level of contrast in each iteration. E(X_{ij}) is the mean of the random variable X_{ij} . Therefore, the original pixels x_{ij}^{1} that initiated at iteration n=1 will take the following value in the enhanced image at iteration N as:

$$x_{ij}^{N} = x_{ij}^{1} + \gamma \sum_{n=1}^{N} x_{ij}^{n} p(x_{ij}^{n}) \tag{15}$$

To calculate the intensity range d, assume the value of the tested pixel x_{ij} with respect to that of its neighboring pixels mostly has one of the following situations:

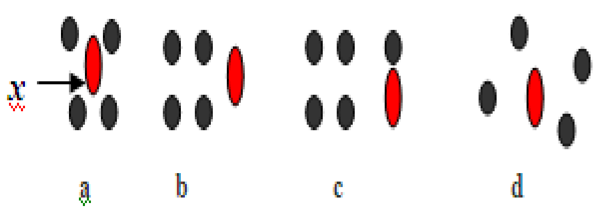

Fig.1 Possible intensity value of the tested pixel x with respect to its neighbors,(a) x has similar value with others,(b) x has far value but the others similar,(c) x has far values with other few pixels,(d) all the pixels are far from each other.

It is clear that if d is taken as the average distance between the tested pixel and its neighboring in the window W as: and m_{ij} is calculated by 5, then we find that:

$$d = \frac{\sum_{y\varepsilon W} \left| y - x_{ij} \right|}{km - 1} \tag{16}$$

$$m_{ij}^{a} > m_{ij}^{b} > m_{ij}^{c} > m_{ij}^{d} \tag{17}$$

It means equation 6 is a proper choice for finding different pmf"s for different pixels in different locations.

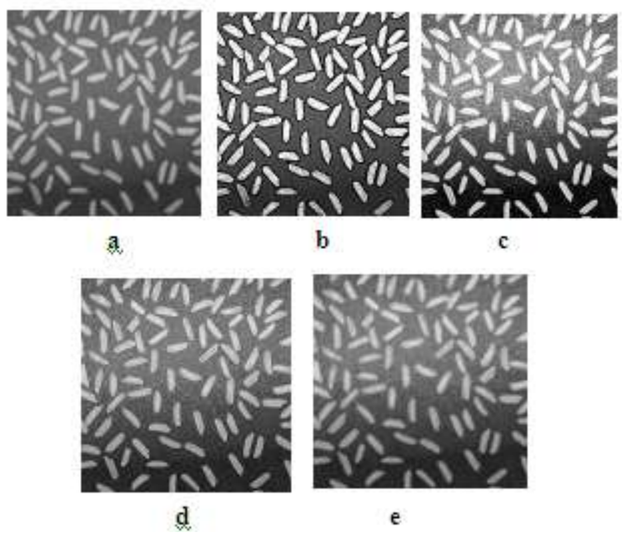

Fig.2 Comparison between the new method with the others subjectively and objectively:(a) original, DE =7.0323,(b) New after one iteration $\gamma = 1$, DE=7.1959, AMBE= 0.1637,(c) GHE,DE=6.938 AMBE= 17.474 ,(d) BBHE, DE= 6.8750 , AMBE= 2.3843, (e) BBMMHE, DE= 6.8177 , AMBE= 0.6216

3. SIMULATION RESULTS

To evaluate the proposed algorithm, it is compared subjectively and objectively with other three known methods. Two measures are used to objectively compare the new method with the others. The first one is the absolute mean brightness error AMBE to demonstrate the ability of each method in preserving the mean brightness of the original image. As the value of AMBE decreases the results improve. The other one is the discrete entropy DE , which indicates the amount of the image details that the enhanced image includes. To get better results, DE value should be close to the original value. AMBE and DE measures are defined as:

$$AMBE(X,Y) = | E(X) - E(Y) | \tag{18}$$

$$DE(Y) = -\sum_{i=0}^{255} p(y_i) \log p(y_i) \tag{19}$$

Where X and Y denote the original and enhanced images.

Fig.2 illustrates a new experiment conducted to enhance the contrast of the rice image. The original, and the outputs images from each method are shown subjectively and objectively. It is clear that the new method delivers the superlative visual results compared to other methods and achieves better results in terms of AMBE and DE values. The reason is that the proposed method enhances every pixel in the image based on its location. The pixels located in smooth and edge regions, as an example, are enhanced with different ratios and, therefore, contributing to the enhancement of the image outlook by different fractions. Since the new method delivers the closest DE value with respect to that of the original one, as shown in Fig.2, the enhanced version preserves the majority of the image details. Fig. 3 clearly demonstrates that the enhanced version due to the proposed method has the same original structure and details before the enhancement process, but with higher amplitudes. Parameter γ is used herein to control the contrast gain and it can be restricted based on your application as shown in Fig.4. Furthermore, as γ increases , or the number of iterations increases, the gain increases and vice versa.

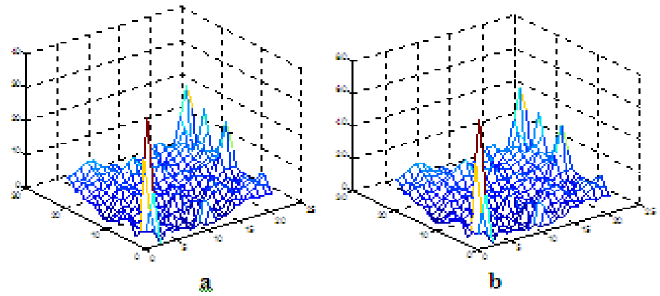

Fig.3 Distribution of group of neighboring pixels before and after enhancing contrast process by the new method:(a)original pixels (b)enhanced version which has the same original look and details

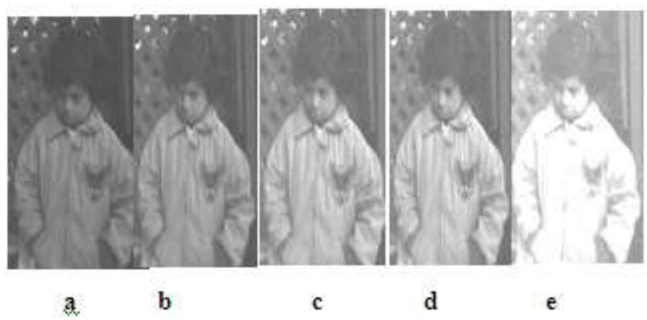

Fig.4 the effect of parameter γ and the performance of each method in enhancing the boy image:(a)original image, DE=4.660 (b)New after one iteration, $\gamma = 0.2$, AMBE = 22.262, DE = 4.6650 ,(c) New after two iterations, $\gamma = 0.2$, AMBE = 49.238, DE = 4.563,(d) New after one iteration, $\gamma = 0.5$, AMBE = 55.574, DE = 4.674, (e) New after one iteration, $\gamma = 1$, AMBE = 104.172, DE = 4.049.

Fig.5 and 6 show the performance of each method in enhancing the contrast of line and moon surface images. The proposed method successfully achieves satisfactory appearance and produces almost natural image, while other methods deliver degraded enhanced images. Moreover, the new method has the closest DE value to that of the original image. Since the output of other methods is degraded, their DE and AMBE do not reflect correct values.

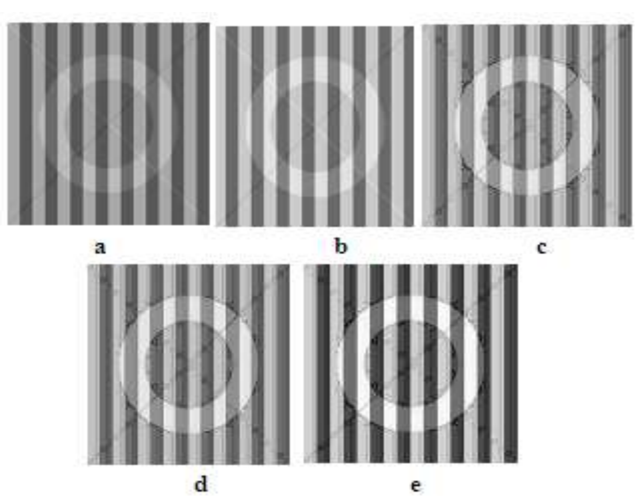

Fig.5 the performance of each method in enhancing the line image contrast:(a) original Line image, DE=2.357 (b)New after one iteration, $\gamma = 0.2$, AMBE = 26.480, DE = 2.372 (c)GHE, AMBE = 9.5049, DE =2.658 (d) BBHE, AMBE = 24.6408, DE =2.707 (e)BBMMHE,AMBE=18.4461, DE = 3.4463

CONCLUSION

In this paper, a new technique is proposed to reveal the hidden details of the tested image by defining a novel definition of probability mass function. The new definition is investigated to enhance the contrast of the tested image and, therefore, to extract the unseen details. Simulation results prove that the proposed method delivers the superlative visual results compared to other methods and, at the same time, preserves the features of the image

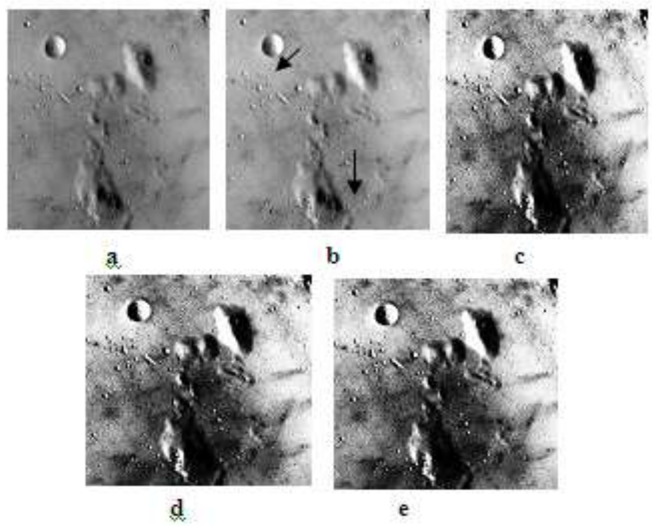

Fig.6 the performance of each method in enhancing the contrast of the moon surface image:(a)original image, DE=5.7412 (b)New after one iteration, $\gamma = 0.2$, AMBE = 25.3924, DE = 5.7428 (c)GHE, AMBE = 1.2739, DE =6.2445 (d) BBHE, AMBE = 7.2816, DE =6.2548 (e) BBMMHE,AMBE=0.6323, DE = 6.2452

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