Survey of Contrast Enhancement Techniques based on Histogram Equalization

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Abstract—**This Contrast enhancement is frequently referred to as one of the most important issues in image processing. Histogram equalization (HE) is one of the common methods used for improving contrast in digital images. Histogram equalization (HE) has proved to be a simple and effective image contrast enhancement technique. However, the conventional histogram equalization methods usually result in excessive contrast enhancement, which causes the unnatural look and visual artifacts of the processed image. This paper presents a review of new forms of histogram for image contrast enhancement. The major difference among the methods in this family is the criteria used to divide the input histogram. Brightness preserving Bi-Histogram Equalization (BBHE) and Quantized Bi-Histogram Equalization (QBHE) use the average intensity value as their separating point. Dual Sub-Image Histogram Equalization (DSIHE) uses the median intensity value as the separating point. Minimum Mean Brightness Error Bi-HE (MMBEBHE) uses the separating point that produces the smallest Absolute Mean Brightness Error (AMBE). Recursive Mean-Separate Histogram Equalization (RMSHE) is another improvement of BBHE. The Brightness preserving dynamic histogram equalization (BPDHE) method is actually an extension to both MPHEBP and DHE. Weighting mean-separated sub-histogram equalization (WMSHE) method is to perform the effective contrast enhancement of the digital image.**

Keywords-component image processing; contrast enhancement; histogram equalization; minimum mean brightness error; brightness preserving enhancement, histogram partition.

I. INTRODUCTION

Image enhancement is a process involving changing the pixels' intensity of the input image, so that the output image should subjectively looks better [1]. The purpose of image enhancement is to improve the interpretability or perception of information contained in the image for human viewers, or to provide a "better" input for other automated image processing systems. There are many image enhancement methods have been proposed. A very popular technique for image enhancement is histogram equalization (HE). This technique is commonly employed for image enhancement because of its simplicity and comparatively better performance on almost all types of images. The operation of HE is performed by remapping the gray levels of the image based on the probability distribution of the input gray levels. It flattens and stretches the dynamic range of the image's histogram and resulting in overall contrast enhancement [2].

However, histogram equalization suffers from major drawbacks especially when implemented to process digital images. Firstly, histogram equalization transforms the histogram of the original image into a flat uniform histogram with a mean value that is in the middle of gray level range. Accordingly, the mean brightness of the output image is always at the middle – or close to it in the case of discrete implementation – regardless of the mean of the input image. For images with high and low mean brightness values, this means a significant change in the image outlook for the price of enhancing the contrast. Secondly, histogram equalization performs the enhancement based on the global content of the image and in its discrete version large bins cannot be broken and redistributed to produce the desired uniform histogram In other words, histogram equalization is powerful in highlighting the borders and edges between different objects, but may reduce the local details within these objects, especially smooth and small ones. Another consequence for this mergence between large and small bins is the production of over enhancement and saturation artifacts [25].

Some researchers have also focused on improvement of histogram equalization based contrast enhancement such as mean preserving bi-histogram equalization (BBHE) [9], equal area dualistic sub-image histogram equalization (DSIHE) [15] and minimum mean brightness error bi-histogram equalization (MMBEBHE) [5], [16]. BBHE separates the input image histogram into two parts based on input mean. After separation, each part is equalized independently. This method tries to overcome the brightness preservation problem. DSIHE method uses entropy value for histogram separation. MMBEBHE is the extension of BBHE method that provides maximal brightness preservation. Though these methods can perform good contrast enhancement, they also cause more annoying side effects depending on the variation of gray level distribution in the histogram [17]. Recursive Mean-Separate Histogram Equalization (RMSHE) [5] is another improvement of BBHE. However, it also is not free from side effects [21].

The mean brightness preserving histogram equalization (MBPHE) methods basically can be divided into two main groups, which are bisections MBPHE, and multi-sections MBPHE. Bisections MBPHE group is the simplest group of MBPHE. Fundamentally, these methods separate the input histogram into two sections. These two histogram sections are then equalized independently. The major difference among the methods in this family is the criteria used to divide the input histogram [9]. Next, Dynamic Histogram Equalization (DHE) technique takes control over the effect of traditional HE so that it performs the enhancement of an image without making any loss of details in it. DHE partitions the image histogram based on local minima and assigns specific gray level ranges for each partition before equalizing them separately. These partitions further go through a repartitioning test to ensure the absence of any dominating portions. This method outperforms other present approaches by enhancing the contrast well without introducing severe side effects, such as washed out appearance, checkerboard effects etc., or undesirable artifacts [21]. The brightness preserving dynamic histogram equalization (BPDHE), which is an extension to HE that can produce the output image with the mean intensity almost equal to the mean intensity of the input, thus fulfil the requirement of maintaining the mean brightness of the image [22].

Multilevel Component-Based Histogram Equalization (MCBHE) where we combine the global histogram equalization, BPBHE, multiple graylevel thresholding, and connected component analysis to produce an image with improved global and local contrast and with minimal distortion [22]. Weighting mean-separated sub-histogram equalization (WMSHE) method is to perform the effective contrast enhancement of the digital image [26].

The paper is organised as follows: HE for digital input image is reviewed together with their mathematical formulation and BBHE, DSIHE, MMBEBHE, and generalization of BBHE, namely - Recursive Mean Separate Histogram Equalization (RMSHE) in section II. Mean Brightness Preserving Histogram Equalization (MBPHE) will be presented in section III and Dynamic Histogram Equalization (DHE) in section IV. Section V includes the Brightness Preserving Dynamic Histogram Equalization (BPDHE) and Multilevel Component-Based Histogram Equalization (MCBHE) in section VI respectively. In section VII, Weighting Mean-Separated Sub-Histogram Equalization (WMSHE) is discussed. Paper concludes with Section VIII containing discussion of various Histogram Equalization techniques.

II. HISTOGRAM EQUALIZATION (HE)

For a given image **X**, the probability density function $p(X_k)$ is defined as

$$p(X_k) = \frac{n^k}{n} \qquad (1)$$

For k = 0, 1… L – 1, where n^k represents the number of times that the level (X_k appears in the input image **X** and n is the total number of samples in the input image. Note that $p(X_k)$ is associated with the histogram of the input image which represents the number of pixels that have a specific intensityX_k. In fact, a plot of n^k vs. X_k is known histogram of **X**. Based on the probability density function, the cumulative density function is defined as

$$c(X) = \sum_{j=0}^{k} p(X_j) \qquad (2)$$

Where X_k = x, for k = 0, 1… L – 1. Note that $c(X_{L-1})$ = 1 by definition. HE is a scheme that maps the input image into the entire dynamic range,(X_0, X_{L-1}), by using the cumulative density function as a transform function. Let's define a transform function $f(x)$ based on the cumulative density function as

$$f(x) = X_0 + (X_{L-1} - X_0)c(x) \qquad (3)$$

Then the output image of the HE, **Y** = {Y $(i, j\}$, can be expressed as

$$\mathbf{Y} = f(\mathbf{X}) \qquad (4)$$
$$= \{f(X(i,j) \mid \forall X(i,j) \in \mathbf{X}\} \qquad (5)$$

The high performance of the HE in enhancing the contrast of an image as a consequence of the dynamic range expansion, Besides, HE also flattens a histogram. Base on information theory, entropy of message source will get the maximum value when the message has uniform distribution property [4]. As addressed previously, HE can introduce a significant change in brightness of an image, which hesitates the direct application of HE scheme in consumer electronics.

A. Brightness Preserving Bi-Histogram Equalization (BBHE)

This method divides the image histogram into two parts as shown in Fig.1. In this method, the separation intensity X_T is presented by the input mean brightness value, which is the average intensity of all pixels that construct the input image. After this separation process, these two histograms are independently equalized. By doing this, the mean brightness of the resultant image will lie between the input mean and the middle gray level [2].

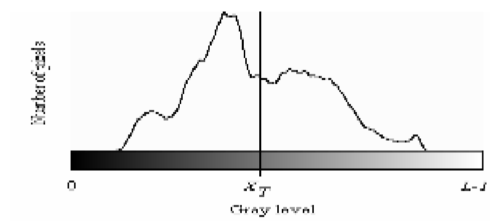

Figure 1.Bi-histogram equalization. The histogram with range from 0 to L-1 is divided into two parts, with separating intensityX_T. This separation produces two histograms. The first histogram has the range of 0 toX_T, while the second histogram has the range of X_{T+1} to L-1.

B. Dualistic Sub-Image Histogram Equalization (DSIHE)

Following the same basic ideas used by the BBHE method of decomposing the original image into two sub-images and then equalize the histograms of the sub-images separately, [4] proposed the so called equal area dualistic sub-image HE (DSIHE) method. Instead of decomposing the image based on its mean gray level, the DSIHE method decomposes the images aiming at the maximization of the Shannon's entropy [5] of the output image. For such aim, the input image is decomposed into two sub-images, being one dark and one bright, respecting the equal area property (i.e., the sub-images has the same amount of pixels). In [4], it is shown that the brightness of the output image O produced by the DSIHE method is the average of the equal area level of the image I and the middle gray level of the image, i.e., L / 2 . The authors of [4] claim that the brightness of the output image generated by the DSIHE method does not present a significant shift in relation to the brightness of the input image, especially for the large area of the image with the same gray-levels (represented by small areas in histograms with great concentration of gray-levels), e.g., images with small objects regarding to great darker or brighter backgrounds.

C. Minimum Mean Brightness Error Bi-HE Method (MMBEBHE)

Still following the basic principle of the BBHE and DSIHE methods of decomposing an image and then applying the HE method to equalize the resulting sub-images independently, [6] proposed the minimum mean brightness error Bi-HE (MMBEBHE) method. The main difference between the BBHE and DSIHE methods and the MMBEBHE one is that the latter searches for a threshold level l_t that decomposes the image I into two sub-images I [0, l_t] and I [l_t +1, L −1], such that the minimum brightness difference between the input image and the output image is achieved, whereas the former methods consider only the input image to perform the decomposition.

Once the input image is decomposed by the threshold level l_t , each of the two sub-images *I [0,* l_t *]* and *I [*l_t *+1, L −1]* has its histogram equalized by the classical HE process, generating the output image. Assumptions and manipulations for finding the threshold level l_t in O (L) time complexity was made in [6]. Such strategy allows us to obtain the brightness l_m (O [O, l] ∪ O [l +1, L −1]) of the output image without generating the output image for each candidate threshold level l, and its aim is to produce a method suitable for real-time applications.

D. Recursive Mean-Separate HE Method (RMSHE)

Recall that the extensions of the HE method described so far in this section were characterized by decomposing the original image into two new sub-images. However, an extended version of the BBHE method named recursive mean-separate HE (RMSHE), proposes the following. Instead of decomposing the image only once, the RMSHE method proposes to perform image decomposition recursively, up to a scale r, generating $2r$ sub-images. After, each one of these sub-images $I^r[l_s, l_f]$ is independently enhanced using the CHE method. Note that when r = 0 (no sub-images are generated) and r = 1, the RMSHE method is equivalent to the CHE and BBHE methods, respectively. In [7], they mathematically showed that the brightness of the output image is better preserved as r increases. Note that, computationally speaking, this method presents a drawback: the number of decomposed sub-histograms is a power of two.

III. Mean Brightness Preserving Histogram Equalization (MBPHE)

The mean brightness preserving histogram equalization (MBPHE) methods basically can be divided into two main groups, which are bisections MBPHE, and multi-sections MBPHE. Bisections MBPHE group is the simplest group of MBPHE. Fundamentally, these methods separate the input histogram into two sections. These two histogram sections are then equalized independently.

However, bisections MBPHE can preserve the mean brightness only to a certain extent. However, some cases do require higher degree of preservation to avoid unpleasant artifacts [7]. Furthermore, bisections MBPHE can only preserve the original mean brightness if and only if the input histogram has a quasi-symmetrical distribution around its separating point [8]. But, most of the input histograms do not have this property. This condition leads to the failure of bisections MBPHE in preserving the mean intensity in real life applications.

Works in [7], [8]-[19] are a few of multi-sections MBPHE. Multi-sections MBPHE group has a better mean brightness preservation as compared with the group of bisections MBPHE. In multi-sections MBPHE, the input histogram is divided into R sub-histograms, where R is any positive integer value. Each sub-histogram is then equalized independently. The creation of the sub-histograms can be carried out recursively (e.g. by using the mean or median intensity value), or based on the shape of the input histogram itself (e.g. using the locations of local maximum or local minimum). Yet, in these methods, the detection of the separating points' process normally requires complicated algorithms, which then associated with relatively high computational time. Furthermore, these methods usually increase the hardware requirement in the implementations for consumer electronic products. In addition, most of these methods put too much constrain on keeping the mean intensity value. As a consequence, not much enhancement could be obtained from most of these methods [20].

IV. Dynamic Histogram Equalization (DHE)

This Dynamic Histogram Equalization (DHE) technique takes control over the effect of traditional HE so that it performs the enhancement of an image without making any loss of details in it. DHE divides the input histogram into number of sub-histograms until it ensures that no dominating portion is present in any of the newly created sub-histograms. Then a dynamic gray level (GL) range is allocated for each sub-histogram to which its gray levels can be mapped by HE. This is done by distributing total available dynamic range of gray levels among the sub-histograms based on their dynamic range in input image and cumulative distribution (CDF) of histogram values. This allotment of stretching range of contrast prevents small features of the input image from being dominated and washed out, and ensures a moderate contrast enhancement of each portion of the whole image. At last, for each sub-histogram a separate transformation function is calculated based on the traditional HE method and gray levels of input image are mapped to the output image accordingly. The whole technique can be divided in three parts – partitioning the histogram, allocating GL ranges for each sub-histogram and applying HE on each of them [21].

V. Brightness Preserving Dynamic Histogram Equalization (BPDHE)

The brightness preserving dynamic histogram equalization (BPDHE), which is an extension to HE that can produce the output image with the mean intensity almost equal to the mean intensity of the input, thus fulfils the requirement of maintaining the mean brightness of the image [22]. This method is actually an extension to both MPHEBP and DHE. Similar to MPHEBP, the method partitions the histogram based on the local maximums of the smoothed histogram. However, before the histogram equalization taking place, the method will map each partition to a new dynamic range, similar to DHE. As the change in the dynamic range will cause the change in mean brightness, the final step of this method involves the normalization of the output intensity. So, the average intensity of the resultant image will be same as the input. With this criterion, BPDHE will produce better enhancement compared with MPHEBP, and better in preserving the mean brightness compared with DHE [22].

VI. Multilevel Component Based Histogram Equalization (MCBHE)

The MCBHE algorithm starts just like the BPBHE algorithm by decomposing the input image *I* into two

Sub images using the original mean brightnessμ_I. We refer to these two sub images as the background I_b and foreground $I_f$sub images, where

$$I = I_b \cup I_f$$

$$I_b(m,n) = \{I(m,n)|I(m,n) < \mu_I, \forall\, I(m,n) \in I\} \quad (6)$$

$$I_f(m,n) = \{I(m,n)|I(m,n) \geq \mu_I, \forall\, I(m,n) \in I\} \quad (6)$$

Unlike BPBHE that equalizes each sub image using the conventional histogram equalization, the gray levels of each sub image in MCBHE are processed using multiple gray level thresholding and connected component analysis. This type of analysis is one of the techniques used in image segmentation applications such as tumor detection [23] and handwriting recognition [24]. In this approach the image under consideration is threshold at multiple predetermined gray levels. At each of these threshold levels, sequential labeling is used to identify those connected components that are below or above the current threshold. Depending on the application and the segmentation objective, some features of these components are extracted and saved to be analyzed later along with values obtained for other components at other levels. The benefit of this approach is that it allows for capturing the change and variation of gray levels within the object as the threshold value is changed. Actually, this is the reason for incorporating this approach in MCBHE, as it will help enhancing the local details [25].

VII. Weighting Mean-Separated Sub-Histogram Equalization (WMSHE)

Weighting mean-separated sub-histogram equalization (WMSHE) method is to perform the effective contrast enhancement of the digital image. This method consist the following steps:

A. *A. Separation of histogram based on our proposed weighting mean function.*

B. *B. Achieving contrast enhancement by equalizing sub-histogram respectively in small-scale detail.*

1) Histogram Separation

Suppose that an input image *W* is composed of *V* discrete gray levels and is denoted by $\{G_0, G_1, ..., G_n, ..., G_{V-1}\}$, the Probability Density Function (*PDF*) and Cumulative Distribution Function (*CDF*) for an input image *W* is expressed as:

$$PDF(G_n) = \frac{n^h}{n}$$

$$\text{where } h = 0, 1, \dots, V-1, \quad (7)$$

Where n^h denotes the number of pixels that correspond to the value *h*, and n *is* the total number of the pixels in the input image *W*. Then the weighting mean value X_t can be calculated by using our proposed weighting mean function, which can be expressed as follows:

$$X_t = \frac{\sum_{l=a}^{b} l \times CDF(l)}{\sum_{l=a}^{b} CDF(l)} \quad (8)$$

Where [*a*, *b*] represents the sub-interval of histogram, l represents the corresponding gray-level, and *t* represents the recursion level. Notice that the sub-interval [*a*, *b*] is initialized as [0, 255] and *t* is initialized as 1. Here we consider that the existing sub-histograms defined over a gray-level range $[X_r, X_{r+1}]$ at the recursion level *t*-1 (0 ≤ *r* ≤ *t*-1). In this paper, the recursion level *t* is experimentally set at 6.

2) Piecewise Transformed Function

After the ideal weighting mean values are determined, we can directly decide the optimum number of sub-images based on the histogram separation, which can be expressed as follows:

$$W_k = \{W(x,y)|\, X_k \leq W(x,y)\, X_{k+1}, \forall\, W(x,y) \in W \quad (9)$$

(9)

Where W_k represents each sub-image, and *k* = 0, 1, 2… *t* – 1. Then the relationship between gray-level *G* and each sub image W_k is defined as the respectivePDF_k:

$$PDF_k(G_h) = \frac{n^k}{n_k} \quad (10)$$

Where *k* = 0, 1… *t* – 1, and *h* =$X_k + 1$, $X_k + 2$, …, X_{k+1}.

Notice that n_h denotes the number of pixels that correspond to the value *h*, and n_k is the total number of the pixels in *k*-th sub image, $PDF_k\ (G_h)$ is associated with the histogram of *k*-th sub image, which represents the frequency of a specific input gray levelG_h. In the next step, the respective CDF_k is defined for each sub-image based on the respective PDF_k.

$$CDF_k(G_j) = \sum_{j=X_0+1}^{n} PDF_k(G_j) \quad (11)$$

Where *k* = 0, 1… *t* – 1, and *h* =$X_k + 1$, $X_k + 2$, …, X_{k+1}..

Finally, the piecewise transformed function is used to map the equalized image. This is characterized by utilizing CDF_k of sub-image W_k for *k* segments [26].

VIII. Discussion

The comparative study of Histogram Equalization based methods shows that the cases which require higher brightness preservation and not handled well by HE, BBHE and DSIHE, have been properly enhanced by RMSHE. MMBEBHE is the extension of BBHE method that provides maximal brightness preservation. Though these methods can perform good contrast enhancement, they also cause more annoying side effects depending on the variation of gray level distribution in the histogram [6].

DHE ensures consistency in preserving image details and is free from any severe side effects. BPDHE can preserve the mean brightness better than BBHE, DSIHE, MMBEBHE, RMSHE, MBPHE, and DHE. MCBHE is simple and heuristic method for contrast enhancement in grayscale images and able to enhance the quality of images such that both global and local contrast is enhanced with minimum distortion in the image appearance [25]. WMSHE achieves the best quality through qualitative visual inspection and quantitative accuracies of Peak Signal-to- Noise Ratio (*PSNR*) and Absolute Mean Brightness Error (*AMBE*) compared to other state-of-the-art methods [26].

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