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Image Inversion and Bi Level Histogram Equalization for Contrast Enhancement

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ABSTRACT

A novel Image Inversion based Two Level Histogram Equalization (IIBLHE) for contrast enhancement is proposed in this paper. In this method, the first level of equalization is carried out in such a way that the image is inversed first and then histogram equalization is applied; again inversed and the second level of equalization is performed by modifying the probability density function of that resultant image by introducing constraints. This technique of contrast enhancement takes control over the effect of global histogram equalization (GHE / HE) so that it enhances the image without causing any loss of details in it. This approach provides a convenient and effective way to control the enhancement process, while being adaptive to various types of images. Experimental results show that the proposed method gives better results in terms of PSNR values when compared to the existing histogram based equalization methods.

Keywords

Contrast Enhancement, Histogram, Histogram Equalization, Probability Density Function (PDF), Cummulative Density Function (CDF)

1. INTRODUCTION

Image enhancement is one of the main areas in digital image processing. Image enhancement is a process that improves the pixels' intensity of the input image, so that the output image looks subjectively better [1]. Image enhancement aims at improving the visual interpretability of information contained in the images. Image enhancement can also be used to provide a better input for other automated image processing systems. Contrast enhancement plays a significant role in image processing for both human and computer vision. It is used as a preprocessing step in medical image processing, speech recognition, texture synthesis and many other image/video processing applications [2 - 5].

Different HE techniques have already been developed for this purpose [6 - 16]. Some of these methods make use of simple linear or nonlinear gray level transformation functions [1], while the rest use complex analysis of different image features such as edge [10], connected component information [11] and so on.

Histogram is defined as the statistical probability distribution of each gray level in a digital image. Histogram Equalization (HE) is a very popular technique for contrast enhancement of images [1, 4, 6 - 9]. It is the most commonly used method due to its computational simplicity and comparatively exhibits better performance on almost all types of images. However, HE is not being recommended to be directly used for the implementation in consumer electronics, such as television since it normally produces undesirable artifacts such as the saturation effect and washed out appearance [19].

The histogram equalization techniques are classified into two principal categories: global and local histogram equalization [13]. Global Histogram Equalization [1] uses the histogram information of the entire input image for its transformation function. Though this global approach is suitable for overall enhancement, it fails to preserve the local brightness features of the input image. When there exists some gray levels in the image with very high frequencies, they are usually dominating the other gray levels with lower frequencies. In such a situation, GHE remaps the gray levels in such a way that the contrast stretching becomes limited in some dominating gray levels having larger image histogram components and causes significant contrast loss for other smaller ones.

Local histogram equalization (LHE) [1] tries to eliminate such problem. It uses a small window that slides through every pixel of the image sequentially and only the block of pixels that fall in this window are taken into account for HE and then the gray level mapping for enhancement is done only for the center pixel of that window. Thus, it makes use of the local information remarkably. However, LHE demands high computational cost and sometimes causes over-enhancement in some portion of the image. Moreover, this technique has the problem of enhancing the noises in the input image along with the image features. The high computational cost of LHE can be minimized using non-overlapping window based HE. Nonetheless, these methods produce an undesirable checkerboard effects on the enhanced images.

Histogram Specification (HS) [1] is another method in which the expected output image histogram can be controlled by specifying the desired output histogram. However, specifying the output histogram pattern is not an easy task as it varies from image to image. A method called Dynamic Histogram Specification (DHS) [16] generates the specified histogram dynamically from the input image. Though this method preserves the original input image histogram characteristics, the degree of enhancement is not significant.

Brightness preserving Bi-Histogram Equalization (BBHE) [8], Recursive Mean Separate HE (RMSHE) [6], Dualistic Sub-Image Histogram Equalization (DSIHE) [14] and Minimum Mean

Brightness Error Bi-Histogram Equalization (MMBEBHE) [15] are the variants of HE based contrast enhancement.

BBHE divides the input image histogram into two parts based on the mean of the input image and then each part is equalized independently. This method tries to overcome the problem of brightness preservation. DSIHE method is similar to BBHE except that it separates the histogram based on the median value. MMBEBHE is another extension of BBHE 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. Recursive Mean-Separate Histogram Equalization (RMSHE) [5] is another improvement of BBHE. However, it is also not free from side effects. In this paper, we propose a technique for contrast enhancement - Image Inversion based Two Level Histogram Equalization (IIBLHE) by combining the advantages of image inversion [19], HE and Constrained PDF based HE (CPHE) [18].

Section 2 details the popular HE techniques. In section 3, the principle of the proposed method is presented. The results and discussions are given in section 4. In section 5, the conclusion is given.

2. HE TECHNIQUES

In this section, some of the existing HE approaches are reviewed in brief. Here, GHE, LHE, BBHE, RMSHE and CPHE are discussed.

2.1. Global Histogram Equalization (GHE)

For an input image F(x, y) composed of discrete gray levels in the dynamic range of [0, L-1], the transformation function $C(r_k)$ is defined as:

$$S_k = C(r_k) = \sum_{i=0}^{k} P(r_i) = \sum_{i=0}^{k} \frac{n_i}{n} \qquad (1)$$

where $0 \le S_k \le 1$ and $k = 0, 1, 2, \ldots, L-1$, n_i represents the number of pixels having gray level r_i, n is the total number of pixels in the input image and $P(r_i)$ represents the Probability Density Function of the input gray level r_i. Based on the PDF, the Cumulative Density Function is defined as $C(r_k)$. The mapping given in equation (1) is called Global Histogram Equalization or Histogram Linearization. Here, S_k can be mapped to the dynamic range of [0, L-1] by multiplying it by (L-1).

Using the obtained CDF values, histogram equalization maps an input level k into an output level H_k using the level-mapping equation (2):

$$H_k = (L - 1) \times C(r_k) \qquad (2)$$

For the traditional GHE described above, the increment in the output level H_k is given by:

$$\Delta H_k = H_k - H_{k-1} = (L - 1) \times P(r_k) \qquad (3)$$

The increment of level H_k is proportional to the probability of its corresponding level k in the original image. For images with continuous intensity levels and PDFs, such a mapping scheme would perfectly equalize the histogram in theory. But, the intensity levels and PDF of a digital image are discrete in practice. In such a case, the traditional HE mapping is not ideal and it results in undesirable effects where the intensity levels with high probabilities often become over-enhanced and the levels with low probabilities get less enhanced and their frequency gets either reduced or even eliminated in the resultant image.

2.2. Local Histogram Equalization (LHE)

GHE takes the global information into account and cannot adapt to local light condition. Local Histogram Equalization (LHE) performs block-overlapped histogram equalization [7, 9]. LHE defines a sub-block and retrieves its histogram information. Then, histogram equalization is applied for the center pixel using the CDF of that sub-block. Next, the sub-block is moved by one pixel and sub-block histogram equalization is repeated until the end of the input image is reached. Though LHE cannot adapt to partial light information [7], still it over-enhances some portions depending on its mask size. However, selection of an optimal block size that enhances all part of an image is not an easy task to perform.

2.3. Histogram Partitioning Approaches

BBHE tries to preserve the average brightness of the image by separating the input image histogram into two parts based on input mean and then equalizing each of the parts independently. RMSHE partitions the histogram recursively. Here, some portions of histogram among the partitions cannot be expanded much, while the outside region expands significantly that creates unwanted artifacts. This is a common drawback of most of the existing histogram partitioning techniques since they keep the partitioning point fixed through out the entire process of equalization.

2.4. Constrained PDF based HE (CPHE)

CPHE [18] is an extension of WTHE [17] which is fast and effective method for image contrast enhancement. In this method, the probability density function of an image is modified by weighting and thresholding prior to HE. This technique provides a convenient and effective mechanism to control the enhancement process, while being adaptive to various types of images.

CPHE method provides a good trade-off between the two features, adaptivity to different images and ease of control, which are difficult to achieve in the GHE-based enhancement methods.

3. IMAGE INVERSION AND BI LEVEL HISTOGRAM EQUALIZATION (IIBLHE)

The proposed method, IIBLHE combines the advantages of image inversion, HE and Constrained PDF based HE (CPHE) [18]. This method is carried out in three steps:

1. Inverse the image
2. Perform HE over the inversed image

3. Re-inverse it and apply CPHE process

If the intensity of the input image is first inversed; equalized using GHE and then the output is re-inversed, mostly the same output will not be generated as the one without intensity inversion process [19]. CPHE is then applied to the re-inversed image as follows:

According to CPHE [18], each original probability density value $P(r_k)$ is replaced by a constrained PDF value $P_c(r_k)$ yielding:

$$\Delta H_k = (L - 1) * P_c(r_k) \quad (4)$$

In the new level-mapping scheme given in (4), $P_c(r_k)$ is obtained by applying a transformation function $\Omega(.)$ to $P(k)$, such that

$$P_c(r_k) = \Omega(P(r_k)) = \begin{cases} P_u & if\ P(r_k) > P_u \\ (\frac{P(r_k) - P_l}{P_u - P_l})^r * P_u & if\ P_l <= P(r_k) <= P_u \\ Average(P(r_k)) & if\ P(r_k) < P_l \end{cases} \quad (5)$$

The transformation function $\Omega(.)$ in equation (5) fixes the original PDF at an upper constraint P_u and at lower constraint P_l and transforms all values between the upper and lower constraints using a normalized power law function with index r>0.

In our level-mapping scheme, the increment for each intensity level is decided by the transformed histogram given in equation (5). The increment can be controlled by adjusting the index r of the power law transformation function. For example, when r<1, the power law function will give a higher weight to the low probabilities in the PDF than the high probabilities. Therefore, with r<1, the less-probable levels are "protected" and the over-enhancement is less likely to occur.

Also in equation (5), the constrained PDF $P_c(r_k)$ is thresholded at an upper limit P_u. As a result, all levels whose PDF values are higher than P_u will have their increment clamped at a maximum value Δ max = $(K - 1) * P_u$ (see equation (4) and (5)). Such upper clamping further avoids the dominance of the levels with high probabilities when allocating the output dynamic range. In our algorithm, the value of P_u is decided by

$$P_u = v * P_{max}, \qquad 0 \le v \le 1 \quad (6)$$

where P_{max} is the peak value (highest probability) of the original PDF and the real number v defines the upper constrain normalized to P_{max}. For example, with v=0.5, the cut-off point is set at 50% of the highest probability observed in the image. A lower value of v results in more number of high-probability levels being clamped and thus the likelihood of their dominance in the output range is less. In our algorithm, the normalized upper constrain v is used as another parameter that controls the effect of enhancement.

The lower constraint P_l in equation (7), is used to find the levels whose probabilities are too low. The P_l value is set to be as low as 0.0001. Instead of taking the value of the lower constraint P_l as zero [18], the mean of $P(r_k)$ has been fixed as lower constraint which is used to improve the contrast of the low probability levels too. The value of P_l is important in controlling the enhancement. It can be observed from equation (5) that when r=1, P_u=1 and P_l=0, the proposed MCPHE reduces to GHE.

The power index r is a major parameter that controls the degree of enhancement. When r<1 (say r=0.5), more dynamic range is allocated to the less probable levels, thus preserving important visual details. The effect of the proposed method approaches that of the GHE, when r is equal to 1. When r>1, more weight is shifted to the high-probability levels and CPHE would yield even stronger effect than the traditional HE. It is useful in specific applications where the levels with high probabilities (e.g., the background) need to be enhanced with extra strength.

The proposed transformation function given in equation (5) introduces constraints to the histogram. This transformation function is applied over the image obtained as a result by carrying out steps 1 and 2. For the proposed IIBLHE method, the upper constraint P_u adapts to P_{max}, the highest probability observed in the image. This mechanism effectively overcomes the necessity of setting the proper constraints manually, resulting in consistent enhancement effect for different types of images.

After the constrained PDF is obtained from equation (5), the cumulative distribution function (CDF) is obtained as:

$$C_c(k) = \sum_{m=0}^{k} P_c(m), \qquad for\ k = 0,1,......., L-1 \quad (7)$$

Now, the modified HE procedure is given as:

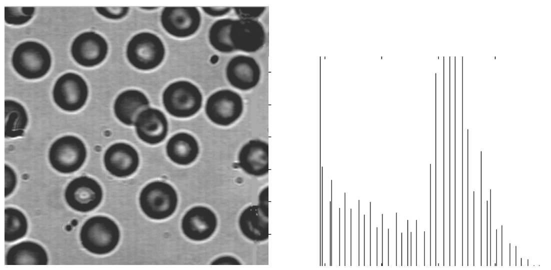
$$F'(i,j) = (L-1) * C_c(F(i,j)) + M_f \quad (8)$$

where M_f is the median adjustment factor, which is introduced to compensate the change of luminance after enhancement. The M_f value is decided by calculating the median value of the enhanced image F′(i, j) from equation (8) while assuming initially M_f as zero. Then the difference between it and the median value of original image is calculated. M_f is now set equal to this median difference. This will not cause serious level saturation (clipping) to the resulting contrast enhanced image.

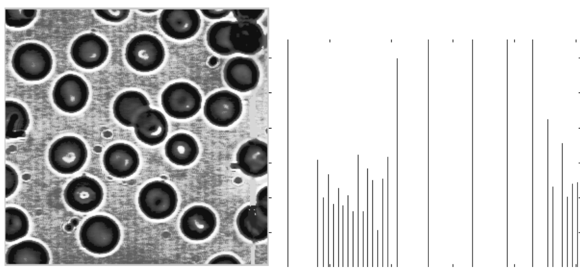
4. RESULTS AND DISCUSSION

We conducted experiments using our method IIBLHE on standard images blood1and ic. To compare the performance of IIBLHE, the same images are enhanced with the contemporary enhancement techniques GHE, BBHE, RMSHE and CPHE. For all these methods, the performance is qualitatively measured in terms of human visual perception and by quantitatively using Peak Signal-to-Noise Ratio (PSNR) values as shown in Table 1.

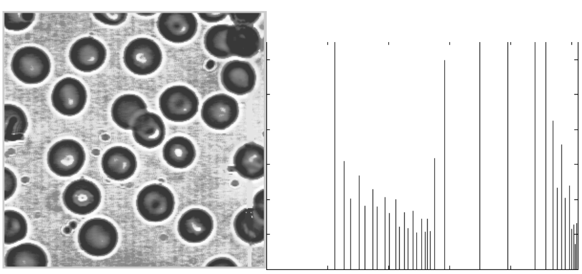
The original blood cell image and its histogram are given in Figure 1(a). The enhanced images of the same by GHE, BHE, RMSHE and CPHE are shown in Figure 1(b) – 1(e) respectively. It is evident from the visual comparison that BHE exhibits better performance than GHE due to its partition-based enhancement. Moreover, it is apparent from Fig 1(d) that RMSHE introduces unwanted artifacts in the enhanced image. CPHE exhibits better results. However, it is noted that IIBLHE (Figure 1(f)) shows better results in terms of visual perception and PSNR value when compared to those of GHE, BHE, RMSHE and CPHE. From Figure 1(e) and 1(f), the variations in the histograms clearly indicate the degree of enhancement.



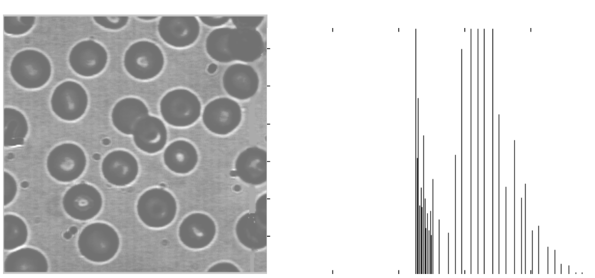
(a)



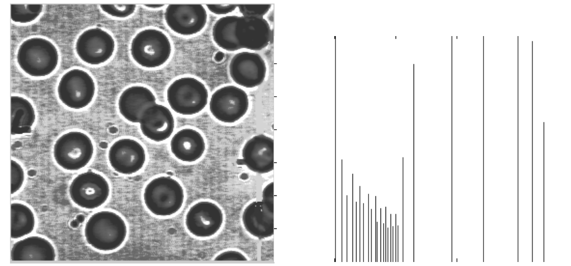
(b)



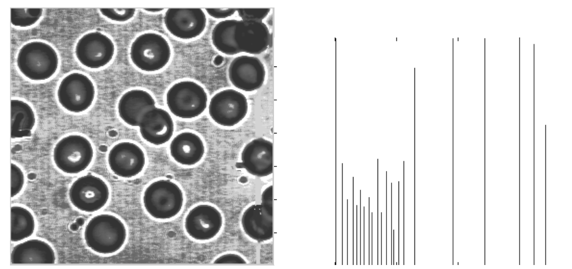
(c)



(d)



(e)



(f)

Figure1: Blood cell images and their corresponding histograms: (a) Original, results of (b) HE (c) BBHE (d) RMSHE (e) CPHE (f) Proposed IIBLHE methods

Table 1. PSNR values of Different Methods

Image/HE	Blood1	IC
GHE	18.2536	16.2672
BBHE	17.3717	16.7699
RMSHE	17.8458	16.9788
CPHE	19.0046	17.1183
IIBLHE	19.1180	17.2992

5. CONCLUSION

The proposed IIBLHE contrast enhancement method is proved to be an efficient approach for low contrast images. Experimental results on standard images show that the degree of enhancement measured in terms of PSNR values for the proposed method is higher than the existing histogram based equalization techniques. This method enhances the images without losing the details of the input images after enhancement. Hence, this method can be used to enhance the images of real-time applications.

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