Constrained PDF based histogram equalization for image constrast enhancement

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Abstract: Histogram Equalization (HE) has proved to be a simple image contrast enhancement technique. However, it tends to change the mean brightness of the image to the middle level of the gray level range. In this paper, a smart contrast enhancement technique based on conventional HE algorithm is proposed. This Constrained PDF based Histogram Equalization (CPHE) 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. In the proposed method, the probability distribution function (histogram) of an image is modified by introducing constraints before the histogram equalization (HE) is performed. This shows that such an approach provides a convenient and effective mechanism to control the enhancement process, while being adaptive to various types of images. Experimental results are presented and compared with results from other contemporary methods.

Keywords: Contrast enhancement; histogram; histogram equalization; probability density function; cummulative distribution function.

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1. INTRODUCTION

Contrast enhancement is an important area in image processing for both human and computer vision. It is widely used for medical image processing and as a preprocessing step in speech recognition, texture synthesis, and many other image/video processing applications [1], [2], [10], [13]. Different methods have already been developed for this purpose [3] - [7], [9], [11], [12], [14] - [18]. Some of these methods make use of simple linear/nonlinear gray level transformation functions [9] while some of the others use complex analysis of different image features such as edge [4], connected component information [16] and so on.

A very popular technique for contrast enhancement of images is histogram equalization (HE) [6], [7], [9], [15], [17]. It is the most commonly used method due to its simplicity and comparatively better performance on almost all types of images. HE performs its operation by remapping the gray levels of the image based on the probability distribution of the input gray levels [11].

Many researches have already been done on histogram equalization and many methods have already been proposed. Generally, we can classify these methods in two principle categories – global and local histogram equalization [5]. Global Histogram Equalization (GHE) [9] 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 adapt with the local brightness features of the input image. If there are some gray levels in the image with very high frequencies, they dominate the other gray levels having 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 small ones. Local histogram equalization (LHE) [9] can get rid of 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 gray level mapping for enhancement is done only for the center pixel of that window. Thus, it can make remarkable use of local information also. However, LHE requires high computational cost and sometimes causes over-enhancement in some portion of the image. Another problem of this method is that it also enhances the noises in the input image along with the image features. To get rid of the high computational cost, another approach is to apply non-overlapping block based HE. Nonetheless, most of the time, these methods produce an undesirable checkerboard effects on enhanced images [9]. Histogram Specification (HS) [9] is another method that takes a desired histogram by which the expected output image histogram can be controlled. However specifying the output histogram is not a smooth task as it varies from image to image. A method called Dynamic Histogram Specification (DHS) is presented in [3], which generates the specified histogram dynamically from the input image. This method can preserve the original input image histogram characteristics. However, the degree of enhancement is not that much significant.

Some researches have also focused on improvement of histogram equalization based contrast enhancement such as mean preserving bi-histogram equalization (BBHE) [17], equal area dualistic sub-image histogram equalization (DSIHE) [18] and minimum mean brightness error bi-histogram equalization (MMBEBHE) [12]. 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. Recursive Mean-Separate Histogram Equalization (RMSHE) [11] is another improvement of BBHE. However, it also is not free from side effects.

To overcome the aforementioned problems, we have proposed a method in section 3, called Constrained PDF based Histogram Equalization (CPHE). This method is an enhancement of Weighted Thresholded HE (WTHE) presented in [8] which is very fast and produced good results over images when compared to other contemporary methods.

2. HE TECHNIQUES

In this section, we review some of the existing HE approaches in brief. Here we discuss about GHE, LHE, DHS and some methods based on histogram partitioning.

2.1. Global Histogram Equalization (GHE)

Suppose 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

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

where $0 \le S_k \le 1$ and $k = 0, 1, 2, \ldots, L-1$.

In (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 as the Probability Density Function (PDF) of the input gray level r_i. Based on the PDF, the Cumulative Density Function(CDF) is defined as $C(r_k)$. This mapping in (1) is called Global Histogram Equalization (GHE) or Histogram Linearization. Here S_k can easily be mapped to the dynamic range of [0, *L*-1] multiplying it by (*L*-1).

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

$$H_k = (L - 1) \times C(r_k) \tag{2}$$

For the traditional HE described above, the increment in the output level H_k can be easily seen to be

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

That is, the increment of level H_k is proportional to the probability of its corresponding level k in the original image. In theory, for images with continuous intensity levels and PDFs, such a mapping scheme would perfectly equalize the histogram. However, in practice, the intensity levels and PDF of a digital image are discrete. In such a case, the traditional HE mapping is no longer ideal. Instead, it results in undesirable effects where intensity levels with high probabilities often become over-enhanced and the levels with low probabilities get less enhanced, their numbers 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 [9], [15]. 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 [3], still it over-enhances some portions depending on its mask size. Actually, using a perfect block size that enhances all part of an image is not an easy and smooth task to perform.

2.3. Histogram Specification (HS)

Histogram specification is applied when we want to transform the histogram of image into a specified histogram to achieve highlighted gray level ranges.

$$V_k = C(z_k) = \sum_{i=0}^{k} P(r_i) = S_k \quad (4)$$

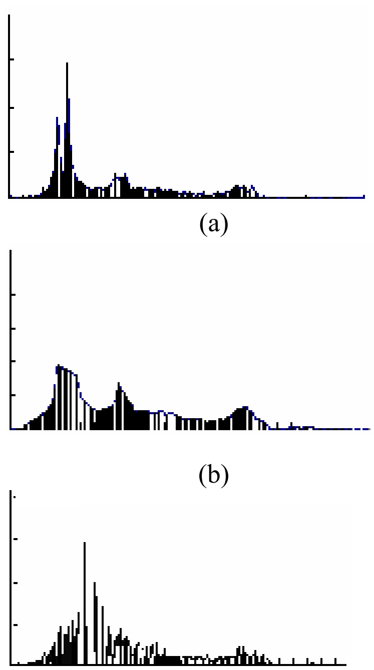
where $k = 0, 1, 2, \ldots, L\text{-}1$.

Note that, S_k and V_k represent the CDFs of histograms of the input image and the specified histogram respectively. We seek the value Z_k that satisfy the following equation

$$Z_k = C^{-1}(s_k) \quad (5)$$

$k = 0, 1, 2, \ldots, L\text{-}1$.

The transformation function for S_k in (4) is same as in GHE and the desired level Z_k (i.e., the mapping of input gray level r_k) is found from (5). Thus, to summarize HS, GHE is performed first on the input histogram and then the gray levels are remapped to the existing gray levels in the specified histogram. Fig. 1 shows how the input image's histogram distribution is specified using the specified histogram. However, to determine the most suitable specified histogram no general rule is available.



(a)

(b)

(c)

Fig. 1. (a) Original Histogram (b) Specified Histogram (c) Result of Specification

2.4. Dynamic Histogram Specification (DHS)

This approach selects some critical points (CP) from the image histogram. Then based on these CPs and other components of the histogram, it creates a specified histogram. Then HS is applied on the image based on this specified histogram. DHS enhances the image keeping some histogram characteristics since the specified histogram is created from the input image histogram. However, as it does not change the dynamic range, the overall contrast of the image is not much enhanced. Moreover, sometimes it causes some artifacts in the images.

2.5. 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. DSIHE partitions the image based on entropy. RMSHE proposes to partition the histogram recursively more than once. Here some portions of histogram among partitions cannot be expanded much, while the outside region expands so much that creates the unwanted artifacts. This is a common drawback of most of the existing histogram partitioning approaches since they keep the partitioning point fixed through the entire process.

3. CONSTRAINED PDF BASED HISTOGRAM EQUALIZATION (CPHE)

The proposed method, Constrained PDF based HE (CPHE) performs histogram equalization based on a modified histogram. Each original probability density value *P(r*$_k$*)* is replaced by a Constrained PDF value *P*$_c$*(r*$_k$*)*, yielding

$$\Delta H_k = (L - 1) * P_c(r_k) \quad (6)$$

In the new level-mapping scheme given in (6), $P_c(r_k)$ is obtained by applying a transformation function $\Omega(.)$ to $P(k)$, such that

$$P_c(r_k) = \Omega(P(r_k)) = \begin{cases} P_u & \text{if } P(r_k) > P_u \\ \left(\dfrac{P(r_k) - P_l}{P_u - P_l}\right)^r & \text{if } P_l <= P(r_k) <= P_u \\ Average(P(r_k)) & \text{if } P(r_k) < P_l \end{cases} \quad (7)$$

The transformation function $\Omega(.)$ clamps 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 (7). The increment can be controlled by adjusting the index r of the power law transformation function. To give an 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 over-enhancement is less likely to occur.

Also in equation (7), 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 $\Delta \max = (K-1) * P_u$ (see equation (6) and (7)). 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

$$P_u = v * P_{max}, \quad 0 \le v \le 1 \tag{8}$$

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 high-probability levels being clamped, and thus the less the likelihood of their dominance in the output range. In our proposed 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 out the levels whose probabilities are too low and thus of little visual importance. Instead of taking the value of the lower constraint P_l as zero [8], the average of $P(r_k)$ has been fixed as lower constraint which is used to improve the contrast of the low probability levels also. The value of P_l is important in controlling the enhancement and is set at a very low fixed value (e.g., 0.01%) in the algorithm. It can be seen from equation (7) that when r=1, P_u =1 and P_l =0 the proposed CPHE reduces to the traditional HE.

In the proposed method, the power index r is the main parameter that controls the degree of enhancement. With $r<1$ (e.g., r=0.5), more dynamic range is allocated to the less probable levels, thus preserving important visual details. When the value of r gradually approaches 1, the effect of the proposed method approaches that of the traditional HE. When $r>1$, more weight is shifted to the high-probability levels, and CPHE would yield even stronger effect than the traditional HE. Using $r>1$ is less common due to its higher likelihood to result in over-enhancement, yet it is still 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 (equation (7)) introduces constraints to the histogram. In [11], a similar approach is adopted but the constraints are manually set by the user. For the proposed CPHE method, the upper constraint P_u adapts to P_{max}, the highest probability observed in the image. Such a mechanism effectively alleviates the necessity of manually setting proper constraints, resulting in consistent enhancement effect for different types of images without manually adjusting the parameters.

After the constrained PDF is obtained from equation (7), the cumulative distribution function (CDF) is obtained by

$$C_c(k) = \sum_{m=0}^{k} P_c(m), \qquad for\ k = 0,1,......., K-1 \tag{9}$$

Now, the classical HE procedure is applied to get the enhanced result.

4. EXPERIMENTAL RESULTS

ASNR (Average Signal to Noise Ratio) is commonly used measure in image enhancement applications, which is given by

ASNR = (f – b)/σ (10)

where **f** is the average gray-level value of the enhanced image.

b is the mean gray-level value of the original image.

σ is the standard deviation.

If the ASNR value is larger, the enhancement method performs better. The following table shows the increased ASNR values from normal HE to CPHE methods for the cameraman image.

Methods	**ASNR value**
Histogram Equalization	0.8924
Bi-histogram Equalization	1.1107
Recursive Mean-Separate HE	1.1864
WTHE	2.4091
Constrained PDF based HE	2.4508

The results from previous techniques and the proposed technique are simulated and compared with the enhancement ability of this proposed method using

Average Signal to Noise Ratio (ASNR) values on variety of images. Here we show some of the results. In Fig. 2(b), HE image shows that the average brightness has increased instead of increasing the contrast. In Fig. 2(c), BHE enhances the image better when one level of partitioning is used. In Fig. 2(d), RMSHE is also not free from generating unwanted artifacts. WTHE in Fig. 2(e) shows relatively good results. On the other hand, CPHE performs much better results with different values of *v.* With increasing the value of *v* the contrast is increasing and making the edges more sharper without introducing any artifacts (Fig. 2(f)).

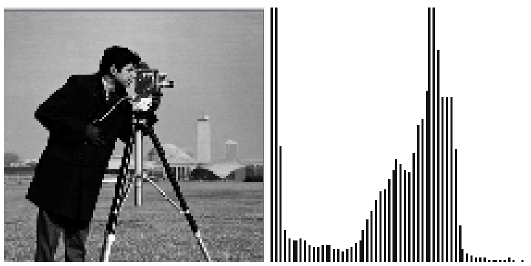


Fig. 2(a) Original Gray Scale Image and its Histogram

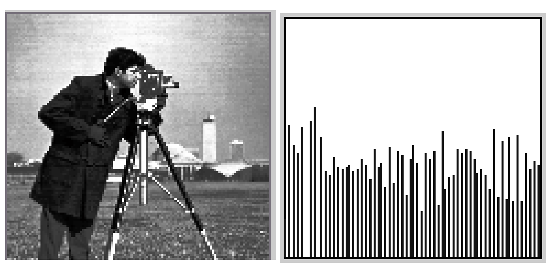


Fig. 2(b) Result of HE & its histogram

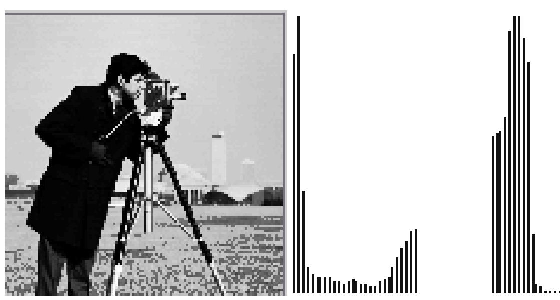


Fig. 2(c) Result of BHE of gray scale image and its histogram

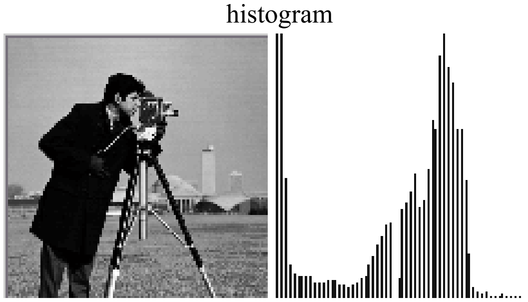


Fig. 2(d) Result of RMSHE r=2 of gray scale image and its histogram

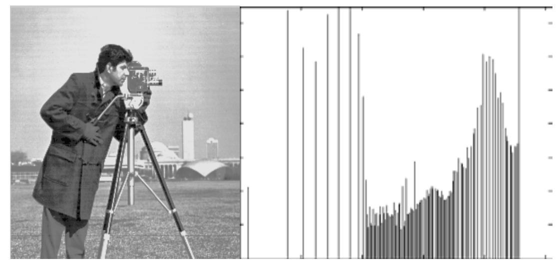


Fig. 2(f) Result of WTHE with r=0.5 and v=0.9 and its histogram

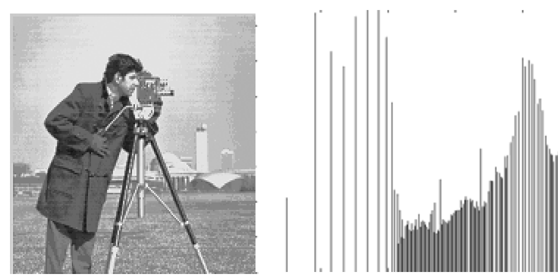


Fig. 2(f) Result of CPHE with r=0.5 and v=0.9 and its histogram

5. CONCLUSION

We have proposed an efficient approach for contrast enhancement of low contrast images. CPHE enhances the image without making any loss in image details. However, if user is not satisfied, he/she may control the extent of enhancement by adjusting the power factor r. Moreover, the method is simple and computationally effective that makes it easy to implement and use in real time systems.

VI. REFERENCES

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