A Dynamic Histogram Equalization for Image Contrast Enhancement

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Abstract — *In this paper, a smart contrast enhancement technique based on conventional histogram equalization (HE) algorithm is proposed. 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 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 though 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*[1].

Index Terms — Contrast enhancement, equalization, normal distribution, histogram partition.

I. 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]-[4]. Different methods have already been developed for this purpose [5]-[17]. Some of these methods make use of simple linear/non-linear gray level transformation functions [6] while some of the others use complex analysis of different image features such as edge [11], connected component information [12] and so on.

A very popular technique for contrast enhancement of images is histogram equalization (HE) [6]-[10]. 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 [5].

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 [14]. Global Histogram Equalization (GHE) [6] 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) [6] 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 [6].

Histogram Specification (HS) [6] 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 [17], 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) [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

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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.

To overcome the aforementioned problems we have proposed a dynamic histogram equalization technique in this paper. Unlike histogram equalization where higher histogram components dominate the lower parts, the proposed dynamic histogram equalization (DHE) employs a partitioning operation over the input histogram to chop it into some sub-histograms so that they have no dominating component in them. Then each sub-histogram goes through HE and is allowed to occupy a specified gray level range in the enhanced output image. Thus, a better overall contrast enhancement is gained by DHE with controlled dynamic range of gray levels and eliminating the possibility of the low histogram components being compressed that may cause some part of the image to have washed out appearance. Moreover, DHE ensures consistency in preserving image details and is free from any severe side effects..

The rest of the paper is organized as follows. Section II gives some of the existing methods, and the proposed DHE is described in Section III. Section IV presents some experimental results of applying DHE and some other method on images, and then the paper concludes in section V.

II. 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.

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

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).

Fig. 2(b) shows that GHE provides a significant improvement in image contrast, but along with some artifacts and undesirable side effects such as washed out appearance in the gray levels of the flower. In (1), larger values of n_k cause the respective gray levels to be mapped apart from each other forcing the mappings of the smaller n_k values to be condensed in a small range with the possibility of duplications. This is the main source of such side effects and loss of image details.

B. Local Histogram Equalization (LHE)

While GHE takes into account the global information and cannot adopt to local light condition, Local Histogram Equalization (LHE) performs block-overlapped histogram equalization [6], [10]. 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 well to partial light information [17], still it over-enhances some portions depending on its mask size. Fig. 2(c) shows the results of applying LHE to Fig 2(a). In Fig. 2(c), the background noises are much enhanced depending on the block size. Actually, using a perfect block size that enhances all part of an image is not an easy and smooth task to perform.

C. 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.

$$v_k = C(z_k) = \sum_{i=0}^{k} P(r_i) = s_k \tag{2}$$

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

$$z_k = C^{-1}(s_k) \tag{3}$$

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

The transformation function for s_k in (2) is same as in GHE and the desired level z_k (i.e., the mapping of input gray level r_k) is found from (3). 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.

D. 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. Fig. 2(d) shows the effect of DHS on an image. Here the overall contrast is not increased significantly. Moreover, as there are some noises (white pixels) in the image, their contributions will be present in the specified histogram, which cause some pixels to be mapped to that gray level in HS. That is why the noises are emphasized here and some portions of the flower become white.

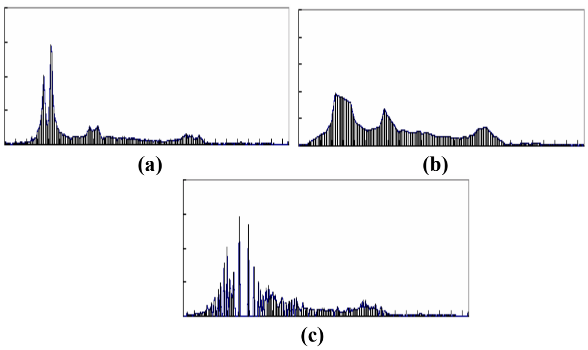

Fig. 1. (a) Original Histogram (b) Specified Histogram (c) Result of Specification.

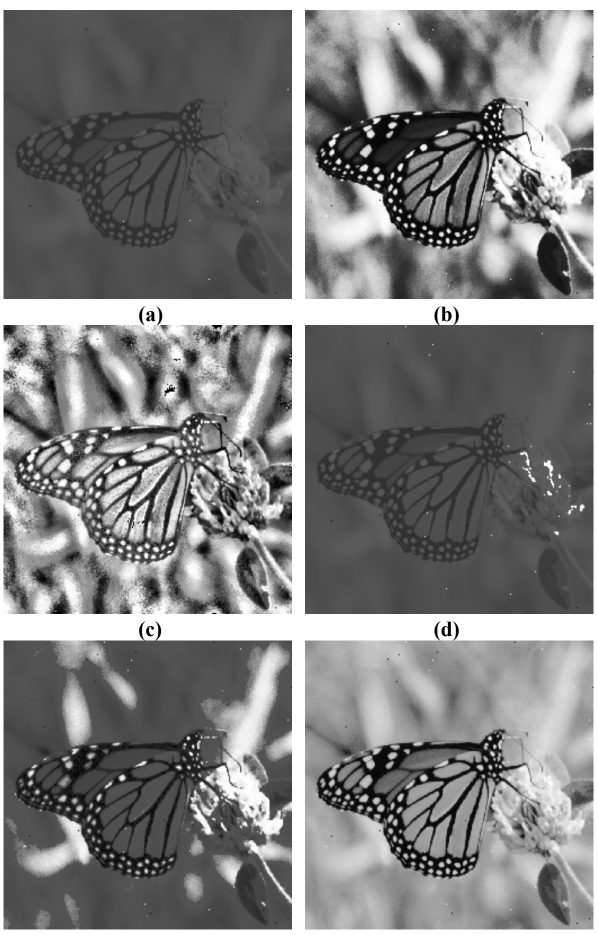

Fig. 2. A set of images showing results of applying different enhancement approaches. (a) Original image (b) GHEed image (c) LHEed image using 32x32 blocks (d) DHSed image (e) RMSHEed image with *r* = 2 (f) DHEed image with *x*= 0.

E. Histogram Partitioning Approaches

As mentioned earlier, 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. Fig. 2(e) shows a result of applying RMSHE with two level (r = 2) of partitioning. The actual effect is depicted in Fig. 3. Here the portion of histogram between partition 2 and 3 cannot expand much, while the outside region expands so much that creates the unwanted artifacts in Fig. 2(e). This is a common drawback of most of the existing histogram partitioning approaches since they keep the partitioning point fixed through the entire process.

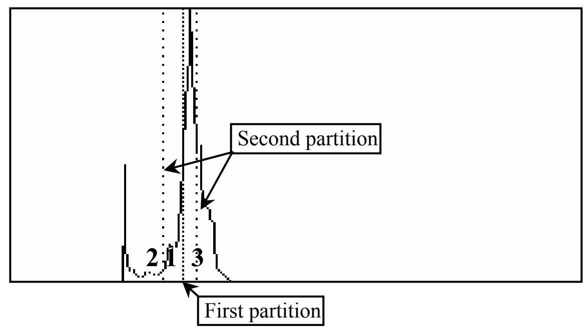

Fig. 3. Partitioning histogram of image in Fig. 1(a) using RMSHE. Dotted lines show portioning (*r* = 2) (1 denotes the first, and 2, 3 denote the 2nd partitioning).

III. DYNAMIC HISTOGRAM EQUALIZATION

In the proposed method, our key observation is to eliminate the domination of higher histogram components on lower histogram components in the image histogram and to control the amount of stretching of gray levels for reasonable enhancement of the image features. In spite of processing the whole histogram with the transformation function at a time, DHE divides it in to a 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.

A. Histogram Partition

DHE partitions the histogram based on local minima. At first, it applies a one-dimensional smoothing filter of size 1 x 3 on the histogram to get rid of insignificant minima. Then it makes partitions (sub-histograms) taking the portion of histogram that falls between two local minima (the first and the last non-zero histogram components are considered as minima). Mathematically, if m_0, m_1, …, m_n are (n+1) gray levels (GL) that correspond to (n+1) local minima in the image histogram, then the first sub-histogram will take the histogram components of the GL range [m_0, m_1], the second one will take [m_1+1, m_2] and so on. These histogram partitioning helps to prevent some parts of the histogram from being dominated by others. One illustration of such partitioning approach is presented in Fig. 4(a).

However, this partitioning alone cannot guarantee the avoidance of domination of some histogram components. To test the presence of any dominating portion, we first find the mean, μ, and standard deviation, σ, of the GL frequencies (histogram components) of each sub-histogram regions. If in a sub-histogram the number of consecutive gray levels having frequencies within the range from $(\mu - \sigma)$ to $(\mu + \sigma)$ becomes more than 68.3% of the total frequency of all gray levels of that sub-histogram, then we can consider it to have a normal distribution of frequencies [18] and there is no dominating portion of histogram that might affect others. However, on the other hand, if this percentage is less than 68.3%, we may be worried about the presence of some dominating portion in the sub-histogram. In this case, DHE splits the sub-histogram into three smaller sub-histograms by partitioning it at gray levels ($\mu - \sigma$) and ($\mu + \sigma$). One such instance is illustrated in Fig. 4(b). Then the first and third sub-histograms are then taken into the same test of domination and re-split if necessary. The middle partition is guaranteed to be domination-free. This histogram splitting operation relieves the low frequency portions of histogram from being at risk of domination when HE performs on it.

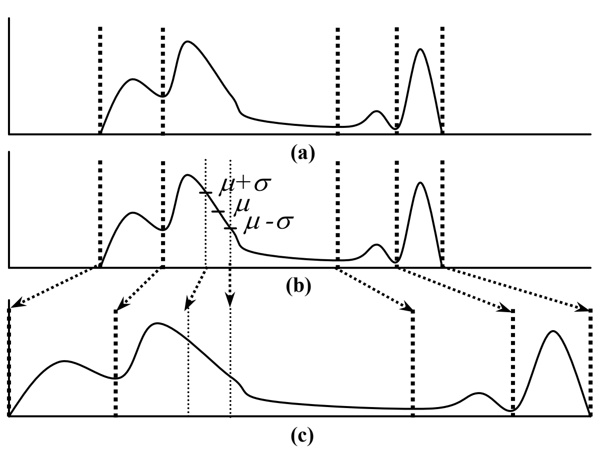

Fig. 4. A pictorial view of proposed DHE. (a) Partitioning into sub-histograms based in local minima, (b) Re-splitting a sub-histogram for not having normal distribution, (c) Gray level range allocation to sub-histograms.

B. Gray Level Allocation

Splitting image histogram into some sub-histograms so that none of them has any dominating portion may not assure a very good enhancement that will be free from domination. This is because some sub-histograms having higher values may stretch too much leaving less room for some other having lower histogram values to get significant contrast enhancement, which is a common phenomena in GHE [6], [14].

For each sub-histogram, DHE allocates a particular range of GLs over which it may span in output image histogram. This is decided mainly based on the ratio of the span of gray levels that the sub-histograms occupy in the input image histogram. Here the straightforward approach is

$$span_i = m_i - m_{i-1} \tag{4}$$

$$range_i = \frac{span_i}{\sum span_i} * (L-1) \tag{5}$$

where,

$span_i$ = dynamic GL range used by sub-histogram i in input image.

m_i = ith local minima in the input image histogram.

$range_i$ = dynamic gray level range for sub-histogram i in output image.

The order of gray levels allocated for the sub-histograms in output image histogram are maintained in the same order as they are in the input image, i.e., if sub-histogram i is allocated the gray levels from [i_{start}, i_{end}], then i_{start} = (i-1)$_{end}$ + 1 and i_{end}= i_{start} + $range_i$. For the first sub-histogram, j, $j_{start} = r_0$. An example of such allocation is presented in Fig. 4(c).

The main goal of contrast enhancement is to distribute the pixel values uniformly in the available dynamic range of gray levels and to result with an output image with linear cumulative histogram [15]. However, if the input image histogram already spans almost the full spectrum of the grayscale, significant visual difference cannot be generated by histogram equalization [6]. The same limitation applies here in DHE if we do not bring any further information in consideration along with the *span* of sub-histograms to allocate grayscale ranges among them. In this situation, *span* of sub-histograms in the input image histogram will be almost the same as the *span* allocated to it in the output image histogram.

Under this circumstance, we give emphasis on the cumulative frequencies (CF) of the GLs in sub-histogram regions. However, giving much importance on the CFs may cause some higher sub-histograms to dominate in the HE. That is why we use a scaled value of CF to perform actively in the allocation process of grayscale ranges among sub-histograms. For gray level range distribution for each sub-histogram, we now use the following factor and ratio instead of *span* in (5)

$$factor_i = span_i * \left(\log CF_i\right)^x \tag{6}$$

$$range_i = \frac{factor_i}{\sum_{k=1}^{t} factor_k} * (L-1) \quad (7)$$

where,

CF_i = the summation of all histogram values of ith sub-histogram.

x = amount of emphasis given on frequency.

Here x is the only parameter that is needed to be adjusted. It determines how much emphasis should be given on CFs to decide the span of each sub-histogram in the output. If the dynamic range of the gray levels of input image is low (which is true for most un-enhanced images), then using *span* alone (i.e., $x = 0$) is sufficient. In other cases x should be given some value. At this point, there will be some loss in image details. It is upon the user that he/she may need to have a better view in any portion of the image without having much care about other parts. We have seen from experiments that a value from 0 to 5 is sufficient for a good enhancement of most images. Thus, the value of x can be set easily without much stress.

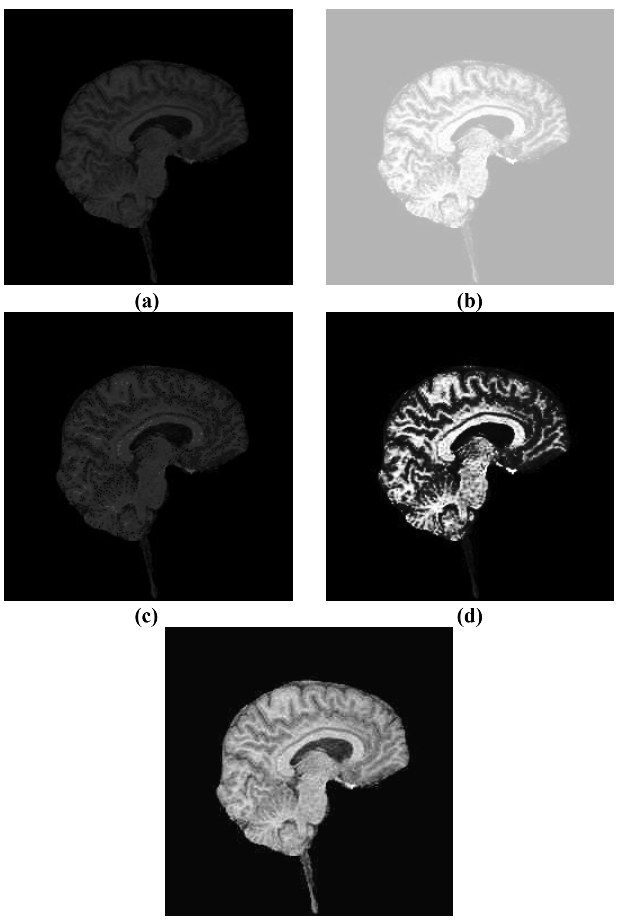

Fig. 5. Simulation results using a brain image. (a) Original image, (b) GHEed image, (c) DHSed image, (d) RMSHEed image (r = 2), (e) DHEed image (x = 0).

C. Histogram Equalization

Conventional HE is applied to each sub-histogram, but its span in the output image histogram is allowed to confine within the allocated GL range that is designated to it. Therefore, any portion of the input image histogram is not allowed to dominate in HE.

Here we may state some key observations on the performance of DHE. Since DHE works on each sub-histogram separately, it prevents over/under enhancements of any portion of the image. It allocates some specific, sequential and non-overlapping gray level ranges to these sub-histograms, which guarantees that no two gray levels from different sub-histograms will map to the same gray level value in the output image. As a result, there will be no significant loss in image details. The sequential assignment and freedom from domination of any portion ensure not having any unpleasant jump in neighboring gray levels in image histogram. Moreover, though different transformation functions are used for equalizing different sub-histograms, DHE ensures that no particular gray level will have, as a whole, multiple mappings in output histogram. Thus, there will be no blocking effect in the image. In this way, though any spatial information is not stored in the image histograms, DHE makes very good enhancement without causing any severe side effect in image.

IV. Experimental Results

The results from previous algorithms and the proposed algorithms are simulated on various images, and compared with the enhancement ability of the proposed approach. Fig. 2 shows the original image along with simulation results from GHE, LHE, DHS, RMSHE and DHE. Here DHE has given better and smooth enhancement of the image.

In Fig. 5 also, we can easily observe that GHE has increased the overall brightness of the image. It has not enhanced the contrast that much. Moreover, it has produced washed out effects in some portion of the image. DHS has not provided a noticeable improvement in the contrast of the image. RMSHE, using r = 2, is also not free from generating unwanted artifacts. On the other hand, the enhancement done by DHE is quite significant enough.

There is another simulation result shown in Fig. 6. Here HEed image shows that the average brightness has increased instead of increasing the contrast. The different concentric rings are more visible and wider than the original image, but still it is not visually pleasing. The DHS method has not improved the contrast of this image rather has introduced some brighter pixels (white spots) in the second ring. LHE has also increased the average brightness of the image, but it has not given a better view. Moreover, it creates some artifacts in the black regions and it has destroyed the center. RMSHE enhances the image the best when one level (i.e., BBHE) of recursive partitioning (r = 1) is used. However, the outer rings are not visible. On the other hand, DHE performs much better role with different values of x. The user can change the value depending on his/her requirement. With increase of x, the different concentric rings' brightness is increasing and making the edges of them sharper without introducing any artifacts. Users may set the value according to desired enhancement.

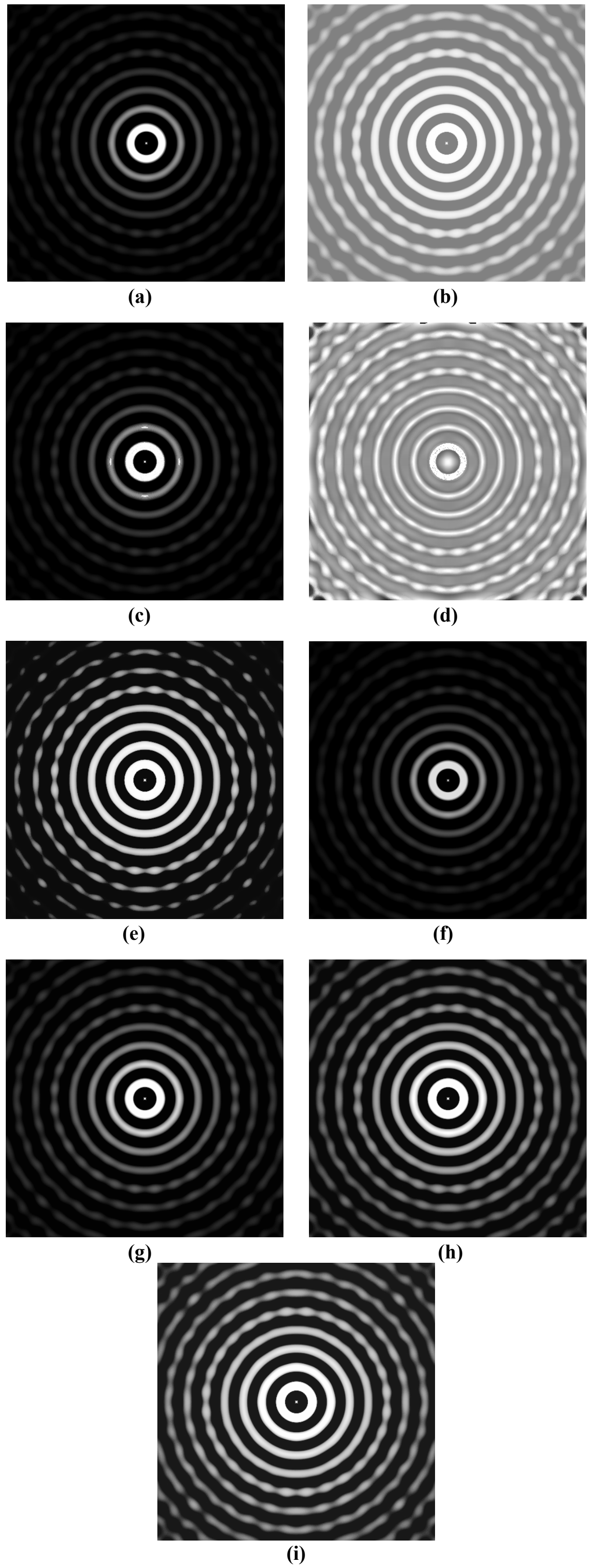

Fig. 6. Simulation results using a synthetic image. (a) Original image (b) GHEed image (c) DHSed image (d) LHEed Image using block size 32x32 (e) RMSHE with one level of recursion (f)-(i) DHEed image with *x* value 0, 1, 3, 5 respectively.

Now we present another set of results that is got by applying the enhancement methods on a natural image.

Fig. 7. Simulation results using a natural image. (a) Original image, (b) GHEed image, (c) BBHEed image, (d) RMSHEed image (*r* = 2), (e)-(h) DHEed image (*x* = 0, 1, 2, 4, accordingly).

In Fig. 7, GHE has improved the text area though the contrast is not that pleasing. Moreover, it has washed out the background. BBHE (i.e., RMSHE using one level of recursive partition) improves the image a bit. Employing more recursions in RMSHE makes it worse. Here DHE shows a better enhancement. The result also shows that the proposed method allows adjusting the value of x to get different degrees of enhancement as well as specifying the amount of loss in image details that user is ready to accept.

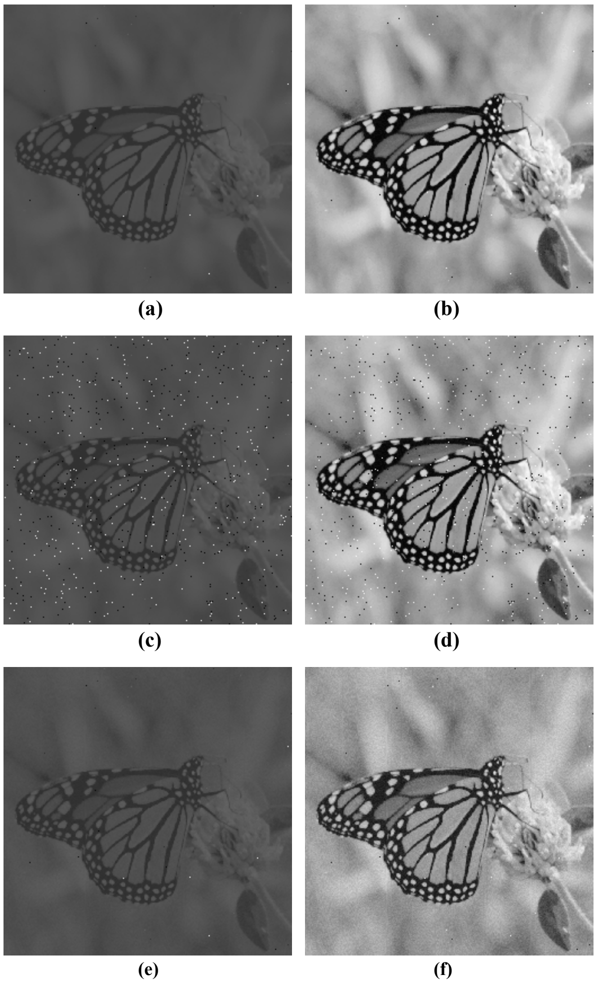

Fig. 8. A set of images showing results of applying DHE on noisy images. (a) Original image (b) Result of applying DHE (x = 0) on (a), (c) Noisy image after adding salt and pepper noise to (a), (d) Result of applying DHE (x = 0) on (c), (e) Noisy image after adding zero mean Gaussian noise to (a), (f) Result of applying DHE (x = 0) on (e).

Fig. 8 shows the robustness of the proposed DHE against noises. Here the histogram partitioning and gray level redistribution technique protect the noise so that it cannot affect image details much during the enhance procedure.

V. CONCLUSION

We have proposed a dynamic approach for contrast enhancement of low contrast images. DHE enhances the image without making any loss in image details. However, if user is not satisfied, he/she may control the extent of enhancement (i.e., the amount of loss of details he/she is ready to accept) by adjusting only one parameter. Moreover, the method is simple and computationally effective that makes it easy to implement and use in real time systems.

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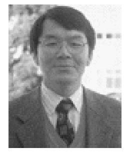

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