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A Fast Method of Contrast Enhancement using Histogram Equalization

Tarun Dewangan

Department of Electronics & Telecom,
Rungta College of Engineering & Technology, Bhilai, India
E-mail: smile4tarun@gmail.com

Abstract

Histogram equalization (HE) has proved to be a simple and effective image contrast enhancement technique. However, it tends to change the mean brightness of the image to the middle level of the gray-level range, which is not desirable in the case of images from consumer electronics products. In the latter case, preserving the input brightness of the image is required to avoid the generation of non-existing artifacts in the output image. To surmount this drawback, Bi-HE methods for brightness preserving and contrast enhancement have been proposed. Although these methods preserve the input brightness on the output image with a significant contrast enhancement, they may produce images with do not look as natural as the input ones. In order to overcome this drawback, this work proposes a novel technique called Multi-HE, which consists of decomposing the input image into several sub-images, and then applying the classical HE process to each one. This methodology performs a less intensive image contrast enhancement, in a way that the output image presents a more natural look. We propose two discrepancy functions for image decomposing, conceiving two new Multi-HE methods. A cost function is also used for automatically deciding in how many sub-images the input image will be decomposed on. Experiments show that our methods preserve more the brightness and produce more natural looking images than the other HE methods.

Index Terms: Contrast enhancement, brightness preserving, histogram equalization, multi-threshold selection.

Introduction

The histogram of a discrete gray-level image represents the frequency of occurrence of all gray-levels in the image [1]. Histogram equalization (HE) is a technique commonly used for image contrast enhancement, since HE is computationally fast and simple to implement. It works by flattening the histogram and stretching the dynamic range of the gray-levels by using the cumulative density function of the image.

Despite its success for image contrast enhancement, this technique has a well-known drawback: it does not preserve the brightness of the input image on the output one.

This drawback makes the use of HE not suitable for image contrast enhancement on consumer electronic products, such as video surveillance, where preserving the input brightness is essential to avoid the generation of non-existing artifacts in the output image. To overcome such drawback, variations of the classic HE technique have proposed to first decompose the input image into two sub-images, and then perform HE independently in each sub-image. These methods, described in details in Section III, use some statistical measures - which consider the value of the gray-levels in the image, during the decomposition step. Another method, which will not be described in Section III but is of relevance for this work, is the variational framework based on histogram transformation for image contrast enhancement and brightness preserving with maximum entropy (BPHEME) presented in [2]. Although in [2] the authors claim that their method is a HE one, we claim that it is actually a histogram specification of an entropy distribution. Both the methods based on Bi-HE and the method proposed in [2] perform image contrast enhancement with success while preserving the input brightness in some extend, but they might generate images with do not look as natural as the input ones. Such result is unacceptable for consumer electronics products. In order to enhance contrast, preserve brightness and produce natural looking images, this article proposes a Multi-HE (MHE) technique which first decomposes the input image into several sub-images, and then applies the classical HE process to each of them. We present two discrepancy functions to decompose the image, conceiving two MHE methods for image contrast enhancement, i.e., Minimum Within-Class Variance MHE (MWCVMHE) and Minimum Middle Level Squared Error MHE (MMLSEMHE). A cost function, taking into account both the discrepancy between the input and enhanced images and the number of decomposed sub-images, is used to automatically make the decision of in how many sub-images the input image will be decomposed on. The remaining of this work is organized as follows. As the proposed method use many concepts previously introduced in the literature, Section II presents some basic definitions regarding gray-level images, whereas Section III describes previous works. The proposed methods are introduced in Section IV. Results of our methods are presented, discussed and compared with other HE methods in Section V. Finally, conclusions are drawn in Section VI.

Previous Work

This section describes some previous works in the literature which make use of the HE method with the purpose of brightness preserving. We start by describing the classical HE (CHE) method in Section III.A. The CHE method was the base for the other four methods, namely BBHE, DSIHE,MMBEBHE and RMSHE, which will be later described in this section. Notice that these four extensions of the CHE method have one main point in common: they decompose the input image into two or more sub-images, and then equalize the histograms of these sub-images independently. In contrast, the major difference among these methods is the criteria they use to decompose the input image into two or more sub-images. The first method, described in Section III.B, divides the input image into two by using its mean gray-level. An extension of this method, which recursively segments the input image, is later described in Section III.E. Section III.C presents a method which uses the equal area value to segment the images, whereas the method described in Section III.D segments images by taking into account the level which yields the minimum brightness error between the input and the enhanced images. To conclude, Section III.F presents some final remarks. Note that, from now on, I and O denote the input (or the original) and the output (or the processed) images, respectively.

Classical HE Method (CHE)

This section describes the CHE method for gray-level images in detail, since this method is the core of this work. The goal of HE method is to uniformly distribute the histogram of an image over the entire range of gray-levels, increasing the image contrast.

The high performance of the HE in enhancing the contrast of an image is a consequence of the dynamic range expansion of the gray-level's image domain. That is, theoretically the output image enhanced by a HE method uses all the gray- level's image domain i.e., from 0 up to L-1 . Besides, the level's image domain, CHE tries to produce an output image with a flatten i.e., a uniform distribution. Based on information histogram, theory, the entropy of a message source will get the maximum value when the message respects the uniform distribution property [4]. This means that an image enhanced by the CHE method has the maximum information (i.e., the entropy) with respect to its original one. However, the CHE method barely satisfies the uniform distribution property in images with discrete gray-level domains.

Despite of the advantages offered the CHE method, it can introduce a significant change in the image brightness, i.e., its mean gray-level. That is, thanks to the uniform distribution specification of the output histogram, the CHE method shifts the brightness of the output image to the middle gray-level, i.e., L/2. This change in brightness is not desirable when applying the CHE scheme into consumer electronics devices, for instance TV and video surveillance. This is because it may introduce unnecessary visual deterioration to the output image.

Brightness Bi-HE Method (BBHE)

In order to overcome the drawback introduced by the CHE method described in the previous subsection, brightness preserving Bi-HE (BBHE) method was proposed in [5]. The essence of the BBHE method is to decompose the original image into two sub-images, by using the image mean gray-level, and then apply the CHE method on each of the sub-images. In [5], it is mathematically shown that the BBHE method produces an output image with the value of brightness (the mean gray-level) located in the middle of the mean of the input image and the middle gray-level (i.e., L/2).

Dualistic Sub-Image HE Method (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 [6] 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 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.

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 CHE method to equalize the resulting sub-images independently, [3] 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 that decomposes the Image into two sub-images, 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, each of the two sub-images has its histogram equalized by the classical HE process, generating the output image.

Recursive Mean-Separate HE Method (RMSHE)

Recall that the extensions of the CHE 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 (see Section III.B) proposed in [7], and 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 2^r sub-images. After, each one of these sub-images is independently enhanced using the CHE method. Note that, computationally speaking, this method presents a drawback: the number of decomposed sub-histograms is a power of two.

Multi-Histogram Equalization Methods for Contrast Enhancement and Brightness Preserving

As mentioned before, the HE method enhances the contrast of an image but cannot preserve its brightness (which is shifted to the middle gray-level value). As a result, the HE method can generate unnatural and non-existing objects in the processed image. In contrast, Bi-HE methods can produce a significant image contrast enhancement and, at some extend, preserve the brightness of the image. However, the generated images might not have a natural appearance. To surmount such drawbacks, the main idea of our proposed methods is to decompose the image into several sub-images, such that the image contrast enhancement provided by the HE in each sub-image is less intense, leading the output image to have a more natural look. The conception of such methods arises two questions.

The first question is how to decompose the input image. As HE is the focus of the work, the image decomposition process is based on the histogram of the image. The histogram is divided into classes, determined by threshold levels, where each histogram class represents a sub-image. The decomposition process can be seen as an image segmentation process executed through multi-threshold selection [8]. The second question is in how many sub-images an image should be decomposed on. This number depends on how the image is decomposed, and so this question is directly linked with the first question. In order to answer these questions, Section IV.A presents two functions to decompose an image based on threshold levels, whereas the algorithm used to find the optimal threshold levels. Finally, a criterion for automatically selecting the number of decomposed sub-images is exposed in Section IV.C.

Multi-Histogram Decomposition

Many HE-based methods have been proposed in the literature to decompose an image into sub-images by using the value of some atistical measure based on the image's gray-level value [3]-[5], [7]. These methods aim to optimize the entropy or preserve the brightness of the image. Here, we will focus our attention on decomposing an image such that the enhanced images still have a natural appearance. For such aim, we propose to cluster the histogram of the image in classes, where each class corresponds to a sub-image. By doing that, we want to minimize the brightness shift yielded by the HE process into each sub-image. With the minimization of this shift, this method is expected to preserve both the brightness and the natural appearance of the processed image.

From the multi-threshold selection literature point of view, the problem stated above can be seen as the minimization of the within-histogram class variance [8], where the within-class variance is the total squared error of each histogram class with respect to its mean value (i.e., the brightness). That is, the decomposition aim is to find the optimal threshold set which minimizes the decomposition error of the histogram of the image into k histogram classes and decomposes the image into k sub-images.

Automatic Thresholding Criterion

This section presents an approach to automatically choose in how many sub-image the original image should be decomposed on. This decision is a key point of our work, which has three main aims:

1. contrast enhancement;
2. brightness preserving;
3. natural appearance.

Nonetheless, these goals cannot be all maximize simultaneously. We take into account that as the number of sub-images in which the original image is decomposed increases, the chance of preserving the image brightness and natural appearance also increases. However, the chances of enhancing the image contrast decrease. To decide on how many sub-images the original image should be decomposed, this tradeoff should be considered. Hence, we propose to use a cost function, initially used in [10], to automatically select the number of decomposed sub-images.

This cost function takes into account both the discrepancy between the original and processed images (which is our own aim decomposition function) and the number of sub-images to which the original image is decomposed, and it is defined as

$$C(k) = \rho(Disc(k))^{1/2} + (\log_2 k)^2,$$

where is a positive weighting constant. The number of k is automatically given as the one decomposed sub-images which minimizes the cost function C (k) it is shown in [10] that the cost function presented in (12) has a unique minimum. Hence, instead of finding the value k which minimizes C(k) throughout k values range, it is enough to k from 0 up to a value where C(k) starts to search for increase.

Original BPHEME MWCVMHE (k = 5) MMLSEMHE (k = 6)

Figure 1: Enhancement for the girl image based on BPHEME, MWCVMHE, and MMLSEMHE methods.

Table 1

Image	Original	RMSHE	MWCVMHE	MMLSEMHE
MEAN	139.2	139.77	139.46	140.05
Standard Deviation	29.7	37.81	35.37	31.47
PSNR	27	28	29.39	33.03

Results

In this section, we report results of experiments comparing our proposed methods with the other HE methods described in Section III and the method proposed in [2]. The input images used in the experiments were the ones previously used in [2]-[5],

[7].

These values were obtained using the threshold criterion for image decomposition exposed in Section IV.B, and weighting constant with the value 0.8 (as done in [10]).

In practice, our methods take less than 50 ms to find the number k, decompose and enhance an image on a Pentium IV - 2GHz.

To start our analysis, for each image, we computed the brightness (the mean) and the contrast (the standard deviation) of the original and the output images obtained by the HE methods. Once the images were analyzed considering their brightness, contrast and PSNR, we performed an image visual assessment. Remark that all the 12 input images, their histograms, their respective enhanced images and equalized histograms, adding up to more than 200 images, can be seen in [13]. Here we present an analysis of 1 image girl. Fig. 1 shows the resulting images obtained by the BPHEME method [4] and our proposed ones for the girl image. Note that the output images obtained by Bi-HE and the RMSHE methods for girl can be observed at Fig. 1. By visually inspecting the images on these two figures, we can clearly see that only the MHE methods (*i.e.*, RMSHE ($r = 2$), MWCVMHE and MMLSEMHE methods) are able to generate natural looking images and still offer contrast enhancement. Fig. 1 shows the Girl image and the resulting images obtained by the MHE methods, *i.e.*, RMSHE ($r = 2$), MWCVMHE and MMLSEMHE. By observing the processed images, it is noticeable that our proposed methods are the only ones among the MHE methods that can produce natural looking images. Recall that the other methods are worst than HE methods for producing natural looking images. Observe that on the upper right corner of the images we can perceive contrast enhancement. Nonetheless, the RMSHE (r = 2) and MWCVMHE methods generate better enhancement on that region than the MMLSEMHE method.

Conclusion

In this work, we proposed and tested a new framework called MHE for image contrast enhancement and brightness preserving which generated natural looking images. The experiments showed that our methods is better on preserving the brightness of the processed image (in relation to the original one) and yields images with natural appearance, at the cost of contrast enhancement. The contributions of this work are threefold: 1) An objective comparison among all the HE methods using quantitative measures, such as the brightness and contrast; 2) An analysis showing the boundaries of the HE technique and its variations (i.e., Bi- and Multi-HE methods) for contrast enhancement, brightness preserving and natural appearance; 3) proposed methods.

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