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A Brief Survey on Different Contrast Enhancement Techniques

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ABSTRACT

Contrast enhancement is used to either increase the contrast of an image with low dynamic range or to bring out image details that would otherwise be hidden. Generally, the contrast enhanced image looks better than the original image. The contrast variations in an image vary with different aspects like illumination, color, scene etc. So many approaches are developed to increase the contrast of an image with abnormal contrast levels. This paper outlines a brief survey over different contrast enhancement approaches. Based on the domain the contrast enhancement takes place, all the earlier approaches are classified as spatial domain and transform domain approaches. Further based on the fashion, they are categorized as local contrast enhancement and global contrast enhancement approaches. All the possible constraints with contrast enhancement techniques is represented here.

Keywords : Contrast Enhancement, Spatial, Transform, Local, Global, Histograms.

I. INTRODUCTION

Image enhancement is one of the challenging issues in low level image processing. Contrast enhancement is the important factor in image enhancement. Contrast enhancement is used to increase the contrast of an image with low dynamic range and bring out the image details that would be hidden. The enhanced image is looks qualitatively better than the original image if the gray-level differences (i.e., the contrast) among objects and background are increased. Contrast enhancement is generally employed as a preprocessing for majority of image processing and in computer vision algorithms. In general, it is difficult to design a visual artifact free contrast enhancement method. To achieve the better quality with reduced computation overhead, there is a necessity of an efficient contrast enhancement design. Image contrast enhancement is the process of transforming gray-levels of an input image so that the corresponding output image would be perceived as having higher contrast. It is expected that the intensity differences of pixels in a local neighborhood would be increased as result of a successful contrast enhancement process. Since the perceived contrast is highly subjective, one may need to alter the contrast of an image according to its own perception. To address this need contrast enhancement algorithms are proposed which can be categorized into three major groups according to the type of transformation (or mapping) applied to the gray-levels (or intensities) of an image: 1) Local contrast enhancement; 2) Global contrast enhancement; and 3) Hybrid contrast enhancement.

Local contrast enhancement algorithms directly alter pixel intensities based on their local properties. Usually transform domain representations are employed for the purpose of intensity manipulation. First a forward transformation on the input image is performed to modify the transform domain coefficients followed by an inverse transformation (or reconstruction) to achieve local contrast enhancement. For this kind of algorithms appropriate settings of the underlying parameters is crucial to avoid the image degradation [1]. On the other hand, global contrast enhancement algorithms usually employ a single mapping function to map input gray levels to output gray-levels.

This paper outlines a brief survey over different contrast enhancement techniques. The complete earlier contrast enhancement approaches are classified as spatial domain and transform domain approaches. A detailed survey about both of these methods is illustrated in this paper. Reminder of the paper is organized as follows; section II describes the details of literature survey. Section III concludes the paper.

II. LITERATURE SURVEY

Contrast enhancement algorithms can be categorized into two major groups according to the data domain they are applied to [2]:

1) Transform-domain algorithms; and

2) Spatial domain algorithms.

A. Transform Domain

Transform-domain algorithms decompose an input image into different subbands so as to modify, globally or locally, the magnitude of the desired frequency components of the image data [3]–[8]. These algorithms enable simultaneous global and local contrast enhancement by transforming the appropriate subbands and in the appropriate scales. The algorithms are computationally complex, and in order to avoid degrading the image, they require appropriate settings of the associated parameters. For example, the centre-surround Retinex [3] algorithm was developed to achieve lightness and color constancy in images, where constancy refers to the perception of color and lightness invariant to spatial and spectral illumination variations. The enhanced image has the benefits of compressed dynamic range and color independent of the spatial distribution of the scene illumination. However, the enhanced image may include “halo” artifacts, especially along boundaries between large uniform regions. A “graying out” can also occur resulting in the image of the scene tending to middle gray.

In [4]–[6], three different transform domain (discrete cosine transform) contrast enhancement algorithms are proposed: a) logarithmic transform histogram matching (LTHM), b) logarithmic transform histogram shifting (LTHS), and c) logarithmic transform histogram shaping using Gaussian distributions (LTHSG). In general, transform domain coefficients are modified according to a mapping of transform domain coefficient distribution to a target distribution and then inverse transform (inverse discrete cosine transform) is applied to obtain contrast enhanced image. In LTHM, target distribution is obtained from transform domain coefficient distribution of histogram equalized input image. A shifted version of transform domain coefficient distribution of input image is used as a target distribution in LTHS and a Gaussian distribution with a mean and standard deviation is employed as a target distribution in LTHSG. The latter algorithms require selection of histogram shift parameter and mean and standard deviation of Gaussian distribution which requires computationally demanding process. Meanwhile, LTHM is a parameter free and its results are comparable with the others [6]. LTHM is designed to mimic the ability of histogram equalization without suffering from the side effects of an over expansion of the dynamic range. This method has the distinct advantage of being incredibly quick with no built in recursion making it a simple and fast solution for image enhancement based on the transform histogram. However, since the histogram of global histogram equalized image in transform domain is used as a target histogram, one can still observe the visual artifacts caused from global histogram equalization. Second-generation wavelets are also used to produce enhanced images without “halo” artifacts.

In edge-avoiding wavelets based contrast enhancement algorithm (EAW) [8], the wavelet coefficients in transform domain are modified and inverse transform is applied to obtain contrast enhanced images. The method achieves both global and local contrast enhancement at the same time with a proper parameter selection. Although the transform-domain contrast enhancement algorithms have shown promising results in a variety of problem domains, due to their computational, memory, and proper parameter setting requirements, image-domain contrast enhancement algorithms are widely used. The conventional approach to enhance the contrast in an image is to manipulate the gray-level of individual pixels according to a specified target histogram.

B. Spatial Domain

The most widely used image-domain contrast enhancement algorithm global histogram equalization (GHE) [1] uses an input-to-output mapping derived from matching of the cumulative distribution function (CDF) of input image histogram to CDF of uniform distribution. Although GHE utilizes the available dynamic range of the image, it tends to over-enhance the image if there are large peaks in the histogram, resulting in a harsh and noisy appearance of the enhanced image.

Local histogram equalization (LHE) algorithms have been developed, e.g., [9], to address the aforementioned problems. These algorithms use a small window that slides over every image pixel sequentially and the histogram of pixels within the current position of the window is equalized. Computational issues aside, LHE sometimes over-enhances some portion of the image and any noise, and may produce undesirable checker-board effects. Human visual system (HVS) is also used to alleviate artifacts of GHE and improve the perceived contrast [10]–[12]. An image is segmented into three regions using a HVS-based thresholding and image equalization is applied to each segment. Processed regions are combined with a weighting to create the final enhanced image. The algorithm's thresholding and merging stages depend on several thresholds which must be carefully selected by a visual observer and/or by local minima of a contrast measure of the output image with respect to the parameters. The parameters are all real valued and it is computationally demanding to select them which makes the algorithm impractical to be applied. Computational efficiency of GHE has made researchers to create methods to alleviate its artifacts. Several algorithms that focus on improving GHE [13]–[15] can achieve satisfactory contrast enhancement. GHE applies histogram specification where contrast enhancement is obtained by suitably changing the image histogram into a desired one. GHE assumes that the target histogram is uniformly distributed. However, GHE fails in providing an efficient histogram specification.

Exact histogram specification (EHS) [13] guarantees that the histogram of the image obtained after enhancement is almost exactly the desired one. However, there does not exist any obvious choice for the desired histogram which is mostly considered as uniform. Although EHS can be used to obtain uniformly distributed output histogram, this does not guarantee that the output will be free of visual artifacts. The original image histogram is modified by weighting and thresholding before the histogram equalization in [14]. The weighting and thresholding are performed by clamping the original image histogram at an upper threshold and at a lower threshold, and transforming all the values between these thresholds using a normalized power law function with an index. We refer the algorithm as weighted thresholded histogram equalization (WTHE). WTHE provides satisfactory enhancement with the carefully selected default parameter setting. Contrast enhancement in histogram modification framework (HMF) [15] minimizes a parameterized cost function to compute a target histogram. The cost function is composed of penalty terms of minimum histogram deviation from the original and uniform histograms, and histogram smoothness. Furthermore, the edge information is embedded into the cost function to weight pixels around region boundaries to address noise and black/white stretching [15].

Different parameter settings will result in different contrast enhancement. Similar to WTHE, adaptive gamma correction with weighting distribution (AGCWD) [16] modifies the input histogram by weighting distribution and enhances image automatically using gamma correction, however, the algorithm may result in loss of details on bright regions of image when there are high peaks in the input histogram. The discrete histogram of an image is transformed to continuous distribution using Gaussian mixture model (GMM) and components of the final GMM is used to obtain sub-regions of the input histogram [17]. A non-linear mapping is applied to each subregion to find the final transformation. Although this process may result in an improvement in perceived contrast, the algorithm is computationally demanding.

Recently, a 2D histogram equalization (2DHE) algorithm which utilities contextual information around each pixel to enhance the contrast of an input image is proposed [2]. 2DHE opened a different direction for contrast enhancement. The algorithm is based on the observation that the contrast in an image can be improved by increasing the gray-level differences between each pixel and its neighboring pixels. The image equalization is achieved by assuming that for a given image, the modulus of the gray-level differences between pixels and their neighboring pixels are equally distributed. GHE is a special case of 2DHE when contextual information is not utilized. The parameter in 2DHE which requires tuning is the size of the spatial neighborhood support which provides the contextual information for a given dynamic range of the enhanced image. Later, the idea of 2D histogram is further improved for the purpose of contextual and variational contrast enhancement (CVC) [18]. A smooth 2D target histogram is obtained by minimizing the parameterized sum of Frobenius norms of the differences from the 2D input histogram, and the 2D uniformly distributed histogram. The contrast enhancement is achieved by mapping the diagonal elements of the 2D input histogram to the diagonal elements of the 2D target histogram. Although parameter dependent results can be found satisfactory, the method is computationally demanding in creating a 2D histogram. This method is further improved by minimizing a complex objective function which considers different factors of the image at the expense of higher computational cost [19]. In general, 2D histogram based methods [2], [18], [19] produce outputs with less visual distortions on them with respect to the methods employing only 1D histogram. However, creating a 2D histogram is computationally demanding and this demand exponentially increases with an increase of size of neighborhood considered [18]. Besides, all the above mentioned methods perform contrast enhancement regardless the level of the contrast available on an image. This may result in degraded contrast in case of image has high level of contrast. Furthermore, contrast enhancement methods are generally utilized as preprocessing step for majority of image processing/ computer vision algorithms, thus, the algorithm should be able to provide satisfactory results with its default parameters. Although carefully selected parameters can help producing satisfactory results for the above mentioned enhancement algorithms, these parameters may have to be adapted from image to image.

Some researchers have also focused on improvement of histogram equalization based contrast enhancement such as mean preserving bi-histogram equalization (BBHE) [26], equal area dualistic sub-image histogram equalization (DSIHE) [27] and minimum mean brightness error bi-histogram equalization (MMBEBHE) [28], [29]. 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 [30]. Recursive Mean-Separate Histogram Equalization (RMSHE) [28] is another improvement of BBHE. However, it also is not free from side effects [31]. 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. 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 [31]. 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 fulfill the requirement of maintaining the mean brightness of the image [32]. Multilevel Component-Based Histogram Equalization (MCBHE) where we combine the global histogram equalization, BPBHE, multiple gray level thresholding, and connected component analysis to produce an image with improved global and local contrast and with minimal distortion [32]. Weighting mean-separated sub-histogram equalization (WMSHE) method is to perform the effective contrast enhancement of the digital image [36].

C. Hybrid Contrast Enhancement

The perceived contrast of an image is unified perception of both local and global contrasts. To achieve this hybrid contrast enhancement algorithm [20] which combines both local and global processes together is proposed. Spatial entropy based contrast enhancement (SECE) in DCT (SECEDCT) algorithm [20] performs global contrast enhancement (SECE) by mapping each input gray-level to an output gray-level using a weight vector computed from a new definition of spatial entropy of gray-levels. This weight for each gray level is calculated using spatial entropy normalized by spatial entropies of other gray-levels. Because of this normalization, the global contrast on output image has slightly improved contrast with respect to the input image. Furthermore, SECE does not consider the spatial relationships of gray-levels; hence, most of the time output is simply linear mapping of the input gray-levels. The global contrast enhanced image is further processed by linearly weighing the transform domain coefficients to achieve local contrast enhancement. SECEDCT does not allow to change the level of global contrast, but the level of local contrast. Later, residual spatial entropy based contrast enhancement (RSECE) is proposed to improve SECE by learning a desired function utilizing both spatial relationships of gray-levels and controlling the level of global contrast enhancement [21]. Similar to SECEDCT, it is extended to DCT domain (RSECEDCT) to achieve both global and local contrast enhancement. The algorithm attempts to perform average brightness-preservation in DCT domain which makes it computationally demanding. Because of brightness preservation and histogram specification process, RSECE may not be able to utilize the entire dynamic range which may result in contrast loss on the output image.

III. CONCLUSION

Contrast enhancement is used to either increase the contrast of an image with low dynamic range or to bring out image details that would otherwise be hidden. The enhanced image looks qualitatively better than the original image as the gray-level differences among objects and background are increased. It is generally employed as a preprocessing for majority of image processing/computer vision algorithms. This paper outlines a detailed literature survey about the contrast enhancement techniques. The overall approaches are categorized as spatial domain, transform domain and hybrid approaches. All the possible advantages and disadvantages of every method is described more clearly.

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