Journal of Engineering Sciences
Vol 10, Issue 11, Nov /2019
ISSN NO:0377-9254

A NOVEL IMAGE ENHANCEMENT TECHNIQUE USING CLAHE WITH GAMMA CORRECTION

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ABSTRACT

In this paper, we propose an adaptive image equalization algorithm that automatically enhances the contrast in an input image using contrast-limited adaptive histogram equalization (CLAHE). We automatically set the clip point for CLAHE based on textureness of a block. Histogram equalization is widely used for contrast enhancement in a variety of applications due to its simple function and effectiveness. Histogram equalization (HE) has proved to be a simple and effective image contrast enhancement technique. However, the conventional histogram equalization methods usually result in excessive contrast enhancement, which causes the unnatural look and visual artifacts of the processed image. We introduce dual gamma correction into CLAHE to achieve contrast enhancement while preserving naturalness. First, we redistribute the histogram of the block in CLAHE based on the dynamic range of each block. Second, we perform dual gamma correction to enhance the luminance, especially in dark regions while reducing over-enhancement artifacts. Since automatic CLAHE adaptively enhances contrast in each block while boosting luminance, it is very effective in enhancing dark images and daylight ones with strong dark shadows. The proposed enhancement method has been shown to perform very well with insufficiently illuminated and noisy images, outperforming other conventional methods, in terms of contrast enhancement and noise reduction in the output image. Experimental results demonstrate that automatic CLAHE with dual gamma correction achieves good performance in contrast enhancement and outperforms state-of-the-art methods in terms of visual quality and quantitative measures.

INTRODUCTION

Dynamic range in digital images can be affected by various factors: intensity of light in the scene (night-time, weather conditions, insufficient lighting), non-uniform exposure (shadows), too short shutter cycle of the camera and too low dynamic range of the sensor or the display device. In all cases, low dynamic range distorts the contrast in the image and results in high noise levels. This often leads to confusion of objects and textures, the inability to segment them and visual illusions, resulting in disorientation, user fatigue, poor detection and classification performance of humans and computer algorithms.

Image contrast enhancement is the key technology to improve visual quality of digital images. It has been widely used in computer vision, pattern recognition, medical imaging, remote sensing imaging and computational photography. Poor image quality is caused by many factors: Poor image sensors, non-uniform exposure, short shutter cycle, and weak ambient light (weather conditions such as heavy clouds, fog, and lack of sunlight or night scenes). Images captured under these circumstances contain contrast distortions, color fading, and low intensity. Above all, captured images under low light condition often have the characteristic of poor dynamic range, low contrast, and strong noise. In practice, the lowlight condition would result in confusions of textures and objects, poor performance of detection, segmentation and annoying visual experience. For better image quality, it is required to enhance the contrast of dark images.

However, histogram equalization suffers from major drawbacks especially when implemented to process digital images. Firstly, histogram equalization transforms the histogram of the original image into a flat uniform histogram with a mean value that is in the middle of gray level range. Accordingly, the mean brightness of the output image is always at the middle – or close to it in the case of discrete implementation – regardless of the mean of the input image. For images with high and low mean brightness values, this means a significant change in the image outlook for the price of enhancing the contrast. Secondly, histogram equalization performs the enhancement based on the global content of the image and in its discrete version large bins cannot be broken and redistributed to produce the desired uniform histogram In other words, histogram equalization is powerful in highlighting the borders and edges between different objects, but may reduce the local details within these objects, especially smooth and small ones. Another consequence for this mergence between large and small bins is the production of over enhancement and saturation artifacts.

In general, image enhancement methods are classified into three categories [1]: Non-linear transfer function-based schemes, histogram-based techniques, and frequency domain methods. Non-linear transfer functions, such as gamma correction and logarithm

mapping, directly modify the pixel values based on regulation [2]. Due to their easy adjustment and efficient implementation, non-linear transfer functions are commonly used for contrast enhancement. Among the nonlinear transfer functions, gamma correction, which effectively represents the properties of the human visual system (HVS), has been widely used in the past several decades. Gamma correction modifies the digital values of dark images to be comfortable for human eyes. Histogram modification transforms a uniform distribution of the gray levels for image contrast enhancement [3], [4], which achieves good performance with low computational complexity. The histogram of an image indicates the relationship between gray levels and their corresponding frequency. The histogram of a gray image $P(j)$ is expressed as follows:

$$P(j) = \frac{n_j}{Num}, \quad j = 0,1,\ldots\ldots,L-1$$

where j denotes the gray level of an image, nj is the number of pixels in the gray level j, and Num is the total number of the image pixels. It is obvious that the histogram is the probability distribution function of j. Based on $P(j)$, histogram equalization (HE) is performed as follows:

The inherent shortcoming of HE is over-enhancement in images with large smooth area, which results in unnaturalness and wash-out appearance. Dark images captured under low light condition contain large smooth area with a narrow dynamic range, and thus HE causes over-enhancement after contrast enhancement. During a couple of decades, several re_nement approaches have been proposed, e.g. brightness preserving bi-histogram equalization (BBHE) [5], equal area dualistic sub-image histogram equalization (DSIHE) [6], and minimum mean brightness error bi-histogram equalization (MMBEBHE) [7]. To overcome the problems of conventional HE, Celik and Tjahjadi [8] used a Gaussian mixture model (GMM) to model the intensity distribution.

EXISTING METHODOLOGY

The robust detection and segmentation of intestinal content in WCE images, together with its further discrimination between turbid liquid and bubbles. Our proposal is based on a twofold system. First, frames presenting intestinal content are detected by a support vector machine classifier using color and textural information. Second, intestinal content frames are segmented into {turbid, bubbles, and clear} regions. The aim of the detection step is to focus the segmentation task in those frame where the intestinal content has been detected, reducing in this way the computation cost of global algorithm.

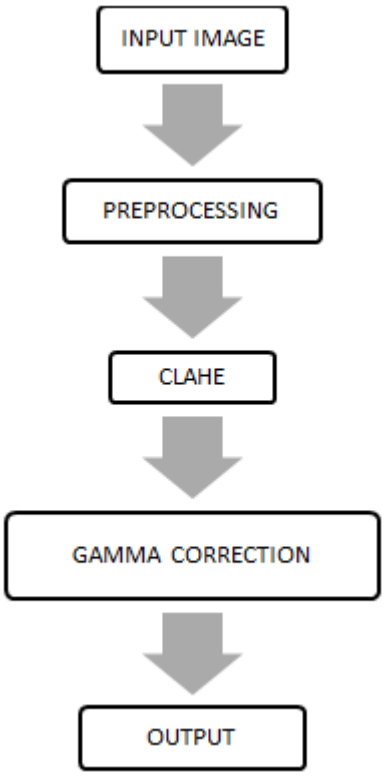
- It only takes into account information local to each pixel through image filters, ignoring useful information from shapes and structures present in the image.
- It is possible to use only the skeleton of the segmentations for the extraction of shape.

PROPOSED METHODOLOGY:

We propose a novel colour feature extraction method to discriminate the bleeding frames from the normal ones, with further localization of the bleeding regions. Our proposal is based on a twofold system. First, we make full use of the color information of WCE images and utilize K-means clustering method on the pixel represented images to obtain the cluster centers, with which we characterize WCE images as words based colour histograms. It is a twofold system. First, we make full use of the color information of WCE images and utilize K-means clustering method on the pixel represented images to obtain the cluster centers.

- Automated or semi-automated segmentation methods would have improvements in efficiency and accuracy.
- Fast, readily available, highest spatial resolution.

BLOCK DIAGRAM:



CLAHE

CLAHE pipeline contains 5 main procedures. First, the image is decomposed into equally-sized rectangular blocks, and histogram adjustment is performed in each block. Histogram adjustment includes histogram creation, clipping, and redistribution. Then, the mapping function is obtained by the cumulative distribution function (CDF) of the clipped histogram. Finally, bilinear interpolation is performed between the blocks to remove possible block artifacts. CLAHE is different from the traditional HE in limiting the contrast by a clip point to cut off the peak value in the histogram of each block. The clipped pixels are redistributed to each gray level. The higher the clip point is, the more the contrast is enhanced as shown in Fig. 2(a). The clip point is calculated as follows:

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100} S_{\max}\right)$$

where M is the number of pixels in each block, N is the dynamic range in this block, $Smax$ is the maximum slope, and α is the clip factor. When α is closed to 0, the clip point would be M/N so that the pixel in this block would be a constant.

CONTENT ADAPTIVE CLIP POINT

In (3), the clip factor α and the maximum slope Smax are used to determine the clip points. We adaptively set different blocks to appropriate clip points, in the manner of assigning homogeneous regions to low clip points and texture blocks to high ones.

The average gray value and standard deviation represent texture ness of a block. Based on them, the block with a larger dynamic range is assigned to a higher clip point value. Thus, we set the clip point adaptively as follows:

$$\beta = \frac{M}{N}\left(1 + P\frac{l_{\max}}{R} + \frac{\alpha}{100}\left(\frac{\sigma}{Avg + c}\right)\right)$$

where σ is the standard deviation of the block; Avg is mean value; and c is a small value to avoid division by 0. The more textural the block is, the bigger σ/Avg is, which is related to a large clip point; $l$max is the maximum value in the block and R represents the entire dynamic range of the image

DUAL GAMMA CORRECTION

Just-noticeable difference (JND) is the minimum difference to be perceived by HVS. We cannot perceive details in dark regions due to the high JND threshold at low intensity [22]. Gamma correction, which is constrained by the parameter ($0 < \gamma < 1$) stretches the difference between gray levels in dark regions. In this case, details in dark regions are enhanced. Gamma correction is formulated as follows:

$$T(l) = l_{\max}\left(\frac{l}{l_{\max}}\right)^{\gamma}$$

In (9), $T(l)$ enhances the low intensity pixels, and the smaller is, the more the pixel values are improved. However, when the pixel values are transformed by gamma correction, pixels in different regions exhibit the same change by the fixed parameter. Although local gamma correction is used, it causes contrast distortions. In this work, we propose dual gamma correction, and introduce it into the CLAHE framework to compensate for contrast distortions. We first define an enhancement weight for the global gray levels of blocks by gamma correction, i.e. 1, as follows:

$$W_{en} = \left(\frac{L_{\max}}{L_{\alpha}}\right)^{1-\gamma_1}$$

where $Lmax$ is the maximum gray value of the image; and $L\alpha$ is the reference gray value. Similar to the median value in [13], we empirically set $L\alpha$ to the gray level where the cumulative density function is 0.75. Next, we obtain the enhanced maximum local $l0$ max by the weighting function Wen. We replace $l$max in (21) with $l0$ max to adjust the dynamic range of the block. Thus, we get the output mapping function $T1(l)$ as follows:

$$l'_{max} = l_{max} \times W_{en}$$
$$T_1(l) = l'_{max} \times cdf(l)$$

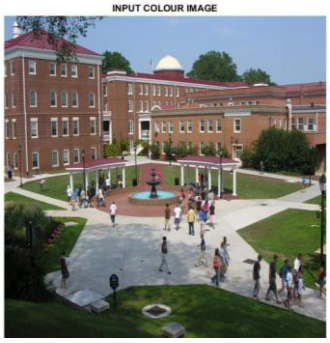
We combine the first gamma correction into the CLAHE framework to prevent tone distortions and over-enhancement. After conducting the first gamma correction in CDF of CLAHE, the image luminance is boosted while the original image features are preserved. It is very effective in enhancing dark regions with textures. However, when the image contains large portion of very dark regions and bright regions together, the under-enhancement problem happens in dark regions. The reason is that 1 mapping curve-based CLAHE increases the contrast without considering content information. To overcome this shortcoming, we perform the second gamma correction for contrast enhancement.

The second gamma correction, i.e. 2, acts as the minimum threshold for contrast enhancement as shown in Fig. 5. We define the second gamma correction function and the final mapping function as follows:

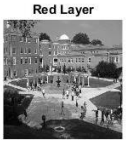
$$Gamma(l) = L_{\max} \times \left(\frac{l}{L_{\max}}\right)^2$$
$$\text{If } r > D_{threshold}, T = \max(T_1(l), Gamma(l))$$
$$\text{else}, T = Gamma(l)$$

EXPERIMENTAL RESULTS

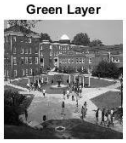
INPUT COLOUR IMAGE



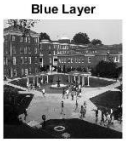
Red Layer



Green Layer

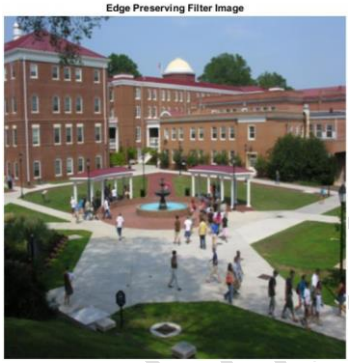


Blue Layer

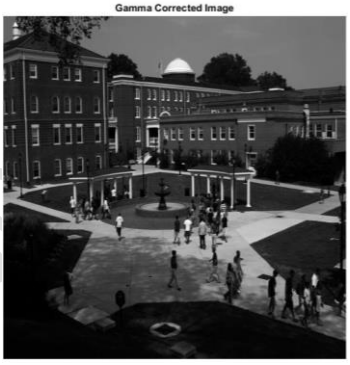


Gray Converted Image

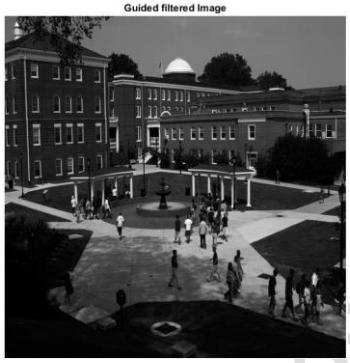
Edge Preserving Filter Image



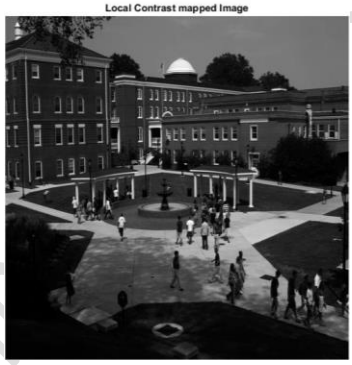
Gamma Corrected Image



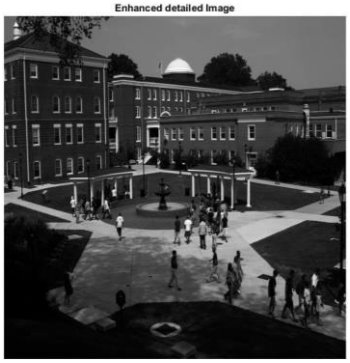
Guided filtered Image



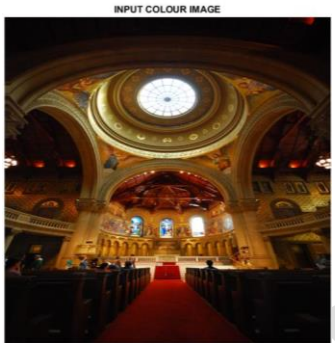
Local Contrast mapped Image



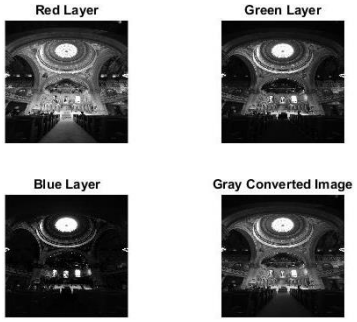
Enhanced detailed Image

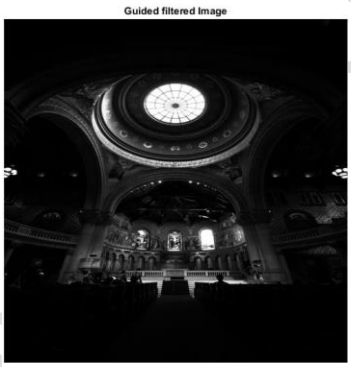


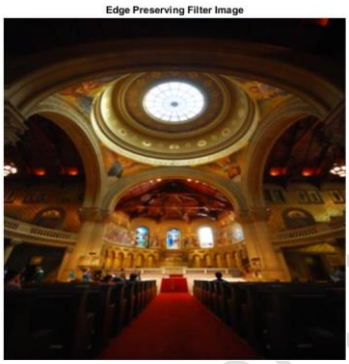
```
Image Quality Assessment
Increased rate of the visible edge of the dehazed image (e): 0.96077%
increased gradient in the dehazed image (r):                 4.6841
Image visibility measurement (IVM):                          5.4841
Image Contrast Gain :                                        0
Visual contrast measure (VCM):                               58.7822
Structural similarity index (SSIM):                          0.83445
```

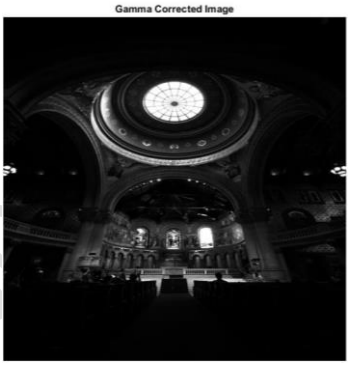


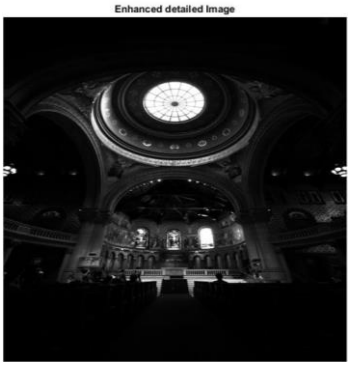
Case 2:











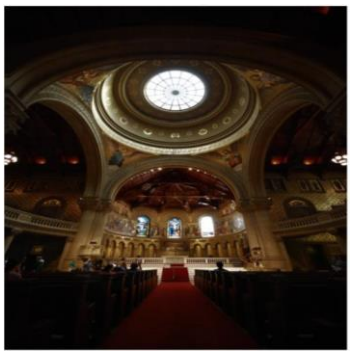


Image Quality Assessment	
Increased rate of the visible edge of the dehazed image (e):	16.7421%
increased gradient in the dehazed image (r):	2207.6527
Image visibility measurement (IVM):	4.6135
Image Contrast Gain :	1
Visual contrast measure (VCM):	46
Structural similarity index (SSIM):	0.73089

CONCLUSIONS

In this paper, we have proposed automatic CLAHE for image contrast enhancement with dual gamma correction. We have introduced dual gamma correction into CLAHE to enhance contrast in an image without tone distortion and over-enhancement. First, we have redistributed the block histogram based on the dynamic range of each block in the CLAHE framework. Second, we have performed the first gamma correction 1 to boost the entire luminance in the image block. Then, we conduct the second gamma correction 2 to adjust the contrast in very dark regions. The proposed method adaptively enhances both contrast and luminance in local regions, and thus is very effective in enhancing dark images and daylight ones with strong dark shadows.

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