Contrast Enhancement for Color Images Using Improved Adaptive Multi-Scale Retinex Algorithm Approach

Murtaza Saadique Basha

Professor, Department of MCA, C.Abdul Hakeem College of Engg. & Tech., Melvisharam, Tamil Nadu, India
Email: *m.s.sadiq[at]gmail.com*

Abstract: ***In this paper, enhancement of the color images using improved adaptive multi-scale retinex algorithm is proposed. This proposed method is an improvement over the classic multi scale retinex algorithm. First, the image is divided into a set of tiles. Two values such as β and α are calculated. The first value represents the minimum intensity for each tile and the second represents the difference between the minimum intensity and maximum intensity for each tile. In the next step, the values of α and β are expanded using bilinear interpolation. Once the values have been expanded, there are still values for each pixel of the MSR image. These values are used to normalize the image. The proposed method enhances the image in an effective way without introducing the halo artifacts and graying. The proposed method is well suited to be implemented on the GPU and by doing so real time processing speeds are achieved.***

Keywords: Contrast Enhancement, Multiscale Retinex, Histogram, Color Images

1. Introduction

The Retinex theory is one of the most famous methods to model and explain how the human visual system perceives color. Retinex theory assumes that eye does not perceive absolute lightness but rather relative lightness [1]. The eye perceives these variations of relative lightness in local areas in the scene. The basic retinex model is based on the assumption that the HVS operates with three retinal-cortical systems, each processing independently the low, middle and high frequencies of the visible electromagnetic spectrum. Every independent process forms a separate image that determines a quality called lightness [1]. Retinex theory based color image enhancement is done in this paper. The paper is structured as follows: the paper starts with introduction to retinex theory and image enhancement in first section. Section 2 presents related works, section 3 elaborates single scale retinex and multiscale retinex methods. Section 4 elaborates our improved retinex model for color image enhancement. Section 5 presents results and discussion. Conclusion is presented in section 6.

2. Related Works

Steve De Backer et al [2] have proposed an image enhancement method based on wavelet least squares estimators. With the evolution of imaging technology, an increasing number of imaging modalities becomes available. The images which contain several image planes are said to be multi component images. Even RGB color images are said to be multi component images as they contain three components. In these types of images, trade-off exists between spectral resolution and signal to noise ratio. Chitwong et al [3] have proposed a contrast enhancement method for minimum mean brightness error from histogram partitioning. First the image is separated by class by calculating the threshold value and each class histogram is then equalized. This method separates the input image's histogram into various groups based on input mean before equalizing them independently. To minimize the absolute mean brightness error (AMBE), the detected peak point is finely adjusted by shifting them in a certain defined range. The result is lowest AMBE value. Tenengrad is also applied to verify the contrast performance. The image performance is higher it Tenegrad value is higher. Agaian et al [4] have proposed an image enhancement algorithm using transform coefficient algorithm. The method fully explores the applications of histogram in image processing. The method comprises three algorithms viz. logarithmic transform histogram matching, logarithmic transform histogram shifting and logarithmic transform histogram shaping using Gaussian distributions. The first algorithm is having 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 image.

Mokhtar et al [5] have proposed image enhancement techniques using local, global, bright, dark and partial contrast stretching of acute Leukemia images. In general leukemia images are blurred, low contrast, hazy and afflicted by unwanted noises. These problems can be invisible and cause difficulty in the interpretation of the important leukemia morphologies, hence increasing false diagnosis. In their method, local and global contrast stretching is performed on the leukemia images and the results are tabulated. Again partial contrast stretching is applied to the input images. This process is repeated using dark contrast stretching and bright contrast stretching. It shows that partial contrast stretching is the best technique that helps to improve the image quality. Goutam Uke and Amit Rajput [6] have proposed a contrast enhancement technique for dark blurred images. Their method consists of two steps. Unsharp masking is the first step where image's edges are sharpened. This brings out hidden details. A 3 x 3 slider map window is applied to the image to determine if the pixel is remapped or not. The new value of remapped pixel is based on sigmoid map function.

1) Retinex Theory

The element of retinex that is exploited to achieve contrast is that eyes exhibit logarithmic response to lightness. This is used by humans to differentiate between indistinct and bright intensities. Retinex based algorithms map intensities using logarithmic mapping [11]. This is done using a response curve that appears more natural to human eyes. The basic formula of single scale retinex is given by the expression

where *I(x,y)* is the input image with 2-dimensions, * defines the convolution operator, *F(x,y)* is the surround function and *R(x,y)* is the output image. The output is the single scale retinex output. The surround function defines the shape and weighing of the average kernel used as a measure of the neighborhood lightness for each pixel. It is observed that the Gaussian function is the best option for surround function as the Gaussian function not only gives the best results but has the advantage of being a separable kernel. A kernel is called a separable kernel if it can be broken down into the convolution of two kernels. This approach reduces the number of computations required to apply the kernel to an image. The Gaussian function is expressed by using the equation

Standard deviation that controls the scale of the surround is σ and K is selected to normalize the kernel such that

The single scale retinex method has certain drawbacks. If the above scale is set too small, the dynamic range compression of the image is very strong but halo effects around the edges are generated. If the scale is set too high, the dynamic range compression of the image is low and graying effect can be seen in more uniform areas. So there is some tradeoff between dynamic compression and color rendition [7]. This single scale retinex cannot provide good tonal rendition and good dynamic compression.

2) Multiscale Retinex

The basic idea behind the multi scale retinex is that multiple surround functions can achieve a good balance between dynamic range compression and tonal rendition. The number of scales can vary from application to application. The basic form of multi-scale retinex is given by the equation

where is the multi scale retinex output, is the output of single scale retinex at different scales, is the different weights associated with different scales, *N* represents the number of scales. And the weights are chosen so that

The final step in the algorithm is to normalize the resulting values to fall between 0 to 1 by using gain / offset scheme as given below

where α represents the gain and β is the offset which is the minimum value in the image and used to ensure that the final β value is 0. α is calculated by dividing 1 with difference between the maximum and minimum values in the MSR output and scaling final image so that its maximum value is 1. The α value is computed globally indicating that this method is the same like histogram equalization. If the image contains areas with different intensities, the global value is not well suited for all the regions of the image [8]. MSR provides dynamic range compression, good tonal rendition and preserves most of the details. But it creates washed out appearance in output images.

3) Improved Adaptive Multiscale Retinex Algorithm

In order to improve the dynamic range compression without incurring the halo artifacts, an improvement over the classic MSR algorithm is proposed. This method uses the adaptive approach to calculate the gain and offset in the final stage of the algorithm and blend the results with globally calculated results [8]. This method uses the adaptive techniques used in Contrast Limited Adaptive Histogram Equalization. The method works as follows:

Step 1: The input image is divided into a set of tiles
Step 2: The minimum intensity for each tile is calculated and assigned as β
Step 3: The difference between maximum and minimum intensities are calculated and assigned as α
Step 4: Expand the field of α and β values to be the same size at the image by using bilinear interpolation
Step 5: Calculate global α and β values
Step 6: Apply expanded α and β values to the image to normalize the image
Step 7: Blend the global and adaptive image

A good dynamic range compression is achieved by applying the adaptive α and β values. These adaptive α and β values are applied to each image tile where the intensities are uniform[10]. This will enhance the noise in that tile. It is observed that, while calculating global α and β values, it is rare that entire image containing uniform intensity.

Figure 1: Overall process of Improved Adaptive Multi Scale Retinex

In order to overcome the above difficulty, the output of global gain or offset values and adaptive (expanded) gain or offset values are blended to achieve a compromise between contrast enhancement and noise enhancement. In order to blend the global and adaptive MSR results, a blend map is used. It is observed that the full sized field of α values gives a good indication of how two MSR images should be blended. Areas with uniform intensity require a very large gain and such areas contain a larger portion of the global MSR output.

Similarly, areas that require low gain value contain a larger portion of the adaptive MSR output. Blend map is produced by first normalizing the interpolated field of gain values by dividing it with maximum gain value. Now the adaptive MSR and global MSR outputs can be blended as a weighted sum which can be seen using the below equation

where ϕ represents the normalized blend map image, represents the global MSR image, represents the MSR of adaptive image and is the MSR of blended image. Expanding the field of α and β values to the same size is done using bilinear interpolation. Bilinear interpolation is a resampling method that uses the distance-weighted average of the four nearest pixel values to estimate a new pixel value. This method is fast and simple to implement to calculate on the GPU.

A decision has to be taken on the number of scales, size of the scale and the weightings of the scale for the MSR algorithm. Only three scales are sufficient to achieve good tonal rendition and dynamic range compression[9]. Standard deviations of 15, 80 and 250 for the scales are used to enhance images under a mega pixel in size [9]. It is observed that these values produce good results but needed to be scaled for images of differing sizes for optimal results. In order to reduce the amount of computation required for the method, the mean value of the entire image is considered instead of computing surround function averages. The mean can be computed efficiently and produces the same results as produced by using large scale value[9].

3. Results and Discussion

As the first step towards the experiment, the image is divided into several segments and each segment is said to be one tile. Since the given image is normal jpeg, the number of tiles can be 9. The original girl image and its tiles are presented below:

Figure 2: Input image

Paper ID: SR241227114646 DOI: https://dx.doi.org/10.21275/SR241227114646

International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2023: 1.843

Figure 3: Different tiles of input image 9 Nos.)

The next step in this method is to find the minimum intensity for each tile and obtained value is assigned as β. The maximum intensity of each tile is obtained and assigned as α. For our example, the minimum intensity of each tile is given in the below table.

Table 1: Minimum, maximum and difference intensity for each tile

Tiles	Minimum Intensity (β)	Maximum Intensity (α)	Difference in Intensity
Tile (1)	62	202	140
Tile (2)	69	212	143
Tile (3)	77	218	141
Tile (4)	51	194	143
Tile (5)	62	220	158
Tile (6)	59	234	175
Tile (7)	49	209	160
Tile (8)	59	207	148
Tile (9)	69	224	155

A point is interpolated using the simple interpolation formula of two pair of points (x_1, x_2) and (y_1,y_2). The formula is

$$y = y_1 + \frac{(y_2 - y_1)(x - x_1)}{(x_2 - x_1)}$$

In order to interpolate the maximum intensity of the first tile, for example, we will use subsequent two maximum intensities are y_1 and y_2, subsequent two minimum intensities as x_1 and x_2. Thus, with x_1=69, x_2=77, y_1=212, y_2=218 & x=62, the interpolated value calculated is 206. This is the new maximum intensity value for tile(1). The same strategy is repeated to calculate the news values of maximum and minimum intensity values of all the tiles of an image. While calculating the maximum intensity value of the tile (4), the output value is 271 whereas the maximum intensity of RGB image is 255. Hence this value has been normalized to 255. The new intensity values of all the tiles are presented in the table below.

Calculating interpolated values of maximum intensity is the vice versa process of above procedure. To interpolate the minimum intensity of the first tile, for example, we will use subsequent two minimum intensities are y_1 and y_2, subsequent two maximum intensities as x_1 and x_2. Thus, with y_1=69, y_2=77, x_1=212, x_2=218 & y=62, the interpolated value calculated is 206. This is the new maximum intensity value for tile (1). The same strategy is repeated to calculate the news values of maximum and minimum intensity values of all the tiles of an image.

Table 2: β, α and intensity difference of each tile (interpolated)

Tiles	Minimum Intensity (β)	Maximum Intensity (α)	Difference in Intensity
Tile (1)	67	206	139
Tile (2)	73	211	138
Tile (3)	87	255	168
Tile (4)	62	255	193
Tile (5)	67	241	174
Tile (6)	68	207	139
Tile (7)	55	190	135
Tile (8)	59	207	148
Tile (9)	69	224	155

The global α and β values are calculated just by finding the average of minimum and maximum intensity values of all the tiles. For the above example, the global α and β values are 67.44 and 221.77 respectively. These values are applied to the expanded α and β values to normalize the image. Below is the normalized image tiles after normalization using the above two values.

Figure 4: Normalized image tiles

The images are concatenated row wise i.e 3 tiles per iteration to get the blended sub images and finally the sub images are blended to get the whole image. The images are blended with same size of tiles. The sub images and the whole image are presented below:

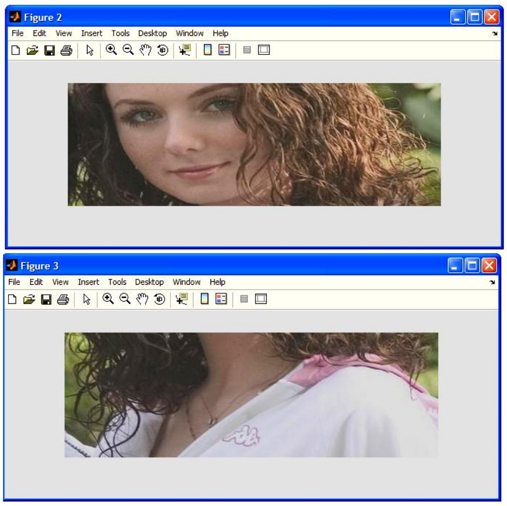

Figure 5: Blending of tiles to form sub images

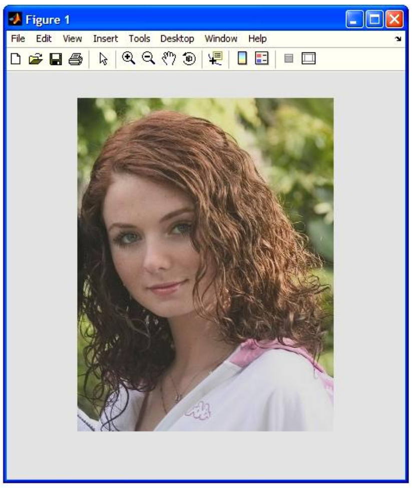

Figure 6: Blended output image

In order to test the contrast of the output images, PSNR is calculated. PSNR defines the effectiveness of the contrast enhancement and compression algorithms. It is the commonly known tool for performance estimation for both the above mentioned algorithms. The below table presents the PSNR of Improved Multi Scale Retinex method and this method is compared with other two traditional contrast enhancement methods such as Single Scale Retinex and Multi Scale Retinex.

Table 3: PSNR values using various methods

Method	PSNR Values
Modified CLAHE	24.01
Single Scale Retinex	22.78
Multi Scale Retinex	25.06
Improved Adaptive Multi Scale Retinex	27.83

4. Conclusion

In this paper, an improved Adaptive Multiscale Retinex technique for color image enhancement and brightness preserving is proposed and tested. The experimental results are tabulated and they show that the performance of Single Scale Retinex (SSR) method is less when compared to the modified CLAHE. Multi Scale Retinex (MSR) method enhances contrast of color images higher than SSR and modified CLAHE. The time and space complexities of the method proposed here comply with real time application requirements. It is also observed that the histogram of improved AMSR method is smooth and contains the same peaks that are available in original image without resulting in saturation at the black or white bounds. The histogram also distributes the peaks very neatly across the intensity range resulting in a high contrast output. The output image looks natural to the human vision.

References

[1] McCann, John J. "Retinex at 50: color theory and spatial algorithms, a review." *Journal of Electronic Imaging* 26, no. 3 (2017): 031204-031204.

[2] De Backer, Steve, Aleksandra Pižurica, Bruno Huysmans, Wilfried Philips, and Paul Scheunders. "Denoising of multicomponent images using wavelet least-squares estimators." *Image and Vision Computing* 26, no. 7 (2008): 1038-1051.

[3] Phanthuna, N., F. Cheevasuvit, and S. Chitwong. "Contrast enhancement for minimum mean brightness error from histogram partitioning." In *Annual Conference on American Society for Photogrammetry and Remote Sensing (March 2009)*. 2009.

[4] Agaian, Sos S., Blair Silver, and Karen A. Panetta. "Transform coefficient histogram-based image enhancement algorithms using contrast entropy." *IEEE transactions on image processing* 16, no. 3 (2007): 741-758.

[5] Mokhtar, Nurhayati, Nor Hazlyna Harun, Mohd Yusoff Mashor, Nazahah Mustafa, Robiyanti Adollah, and Nashrul Fazli Mohd Nasir. "Image enhancement techniques using local, global, bright, dark and partial contrast stretching for acute leukemia images." (2009): 1-7.

[6] Gautam, Manu. "Role and participation of parent teacher association in school management: Evidences from school of Madhya Pradesh." *Madhya Pradesh Journal of Social Sciences* (2014): 76.

[7] Seo, Hae Jong. "EE264 Project: Evolution of Retinex Algorithm and How to connect it to denoising methods." (2007).

[8] Li, Chunming, Rui Huang, Zhaohua Ding, J. Chris Gatenby, Dimitris N. Metaxas, and John C. Gore. "A level set method for image segmentation in the presence of intensity inhomogeneities with application to MRI." *IEEE transactions on image processing* 20, no. 7 (2011): 2007-2016.

[9] Zhang, Qifu, and Haibin Duan. "Biological weight selection of multi-scale retinex via artificial bee colony algorithm." *Optik* 125, no. 3 (2014): 1434-1438.

[10] Sund, Torbjørn, and Karsten Eilertsen. "An algorithm for fast adaptive image binarization with applications in radiotherapy imaging." *IEEE transactions on medical imaging* 22, no. 1 (2003): 22-28.

[11] Kwok, Ngaiming, Haiyan Shi, Gu Fang, Ching-Feng Lin, Chin Yeow Wong, Shilong Liu, and Md Arifur Rahman. "Logarithmic profile mapping and Retinex edge preserving for restoration of low illumination images." In *2016 9th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, pp. 217-222. IEEE, 2016.