CHAPTER 4

CONTRAST ENHANCEMENT FOR COLOR IMAGES USING IMPROVED ADAPTIVE MULTI-SCALE RETINEX ALGORITHM APPROACH

4.1 INTRODUCTION

In this chapter, 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 $\beta$ and $\alpha$ 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 $\alpha$ and $\beta$ 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.
4.2 RETINEX THEORY

The Retinex theory was developed by Land and Mc Cann. It is one of the most famous methods to model and explain how the human visual system perceives color (E.Land and J.J.Mc Cann 1971). Retinex theory assumes that eye does not perceive absolute lightness but rather relative lightness. The eye perceives these variations of relative lightness in local areas in the scene (E.H.Land and J.J.Mc Cann 1971) (E.H.Land 1986)

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 (D.Marini and A.Rizzi 2000).

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. This is done using a response curve that appears more natural to human eyes (E.H.Land and J.J.Mc Cann 1971).

The basic formula of single scale retinex is given by the expression

\[
R_{x,y} = \frac{\log I(x,y)}{\log[F(x,y)I(x,y)]} \tag{4.1}
\]

\[
R_{x,y} = \log I(x,y) - \log[F(x,y)I(x,y)] \tag{4.2}
\]
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 (D.J.Jobson et al 1997).

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 (D.J.Jobson et al 1997). The Gaussian function is expressed by using the equation

$$F(x, y) = K e^{-x^2 + y^2 \over 2\sigma^2}$$

(4.3)

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

$$\int \int F(x, y) \, dx \, dy = 1$$

(4.4)

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 (Hae Jong Seo 2007). This single scale retinex cannot provide good tonal rendition and good dynamic compression (Woodell et al 1997).

4.3 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

\[ R_{MSR}(x, y) = \sum_{n=1}^{N} w_n R_n(x, y) \] (4.5)

where \( R_{MSR}(x, y) \) is the multi scale retinex output, \( R_n(x, y) \) is the output of single scale retinex at different scales, \( w_n \) is the different weights associated with different scales, \( N \) represents the number of scales. And the weights are chosen so that

\[ \sum w_n = 1 \] (4.6)

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

\[ R_{MSR}(x, y) = \alpha \left[ \sum_{n=1}^{N} w_n R_n(x, y) \right] - \beta \] (4.7)

where \( \alpha \) represents the gain and \( \beta \) is the offset which is the minimum value in the image and used to ensure that the final \( \beta \) value is 0. \( \alpha \) 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 $\alpha$ 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 (Mohd Firdaus et al 2010). MSR provides dynamic range compression, good tonal rendition and preserves most of the details. But it creates washed out appearance in output images.

4.4 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 (Mohd Firdaus et al 2010).

This method uses the adaptive techniques used in Contrast Limited Adaptive Histogram Equalization (CLAHE) (A.M.Reza 2004). 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 $\beta$
Step 3 : The difference between maximum and minimum intensities are calculated and assigned as $\alpha$
Step 4 : Expand the field of $\alpha$ and $\beta$ values to be the same size at the image by using bilinear interpolation

Step 5 : Calculate global $\alpha$ and $\beta$ values

Step 6 : Apply expanded $\alpha$ and $\beta$ 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 $\alpha$ and $\beta$ values. These adaptive $\alpha$ and $\beta$ values are applied to each image tile where the intensities are uniform. This will enhance the noise in that tile. It is observed that, while calculating global $\alpha$ and $\beta$ values, it is rare that entire image containing uniform intensity.
Figure 4.1 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 \( \alpha \) 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

\[
R_{MSR_b} = \phi \times R_{MSR_g} + (1 - \phi) \times R_{MSR_a}
\]  

where \( \phi \) represents the normalized blend map image, \( R_{MSR_g} \) represents the global MSR image, \( R_{MSR_a} \) represents the MSR of adaptive image and \( R_{MSR_b} \) is the MSR of blended image.

Expanding the field of \( \alpha \) and \( \beta \) 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. (D.J.Jobson et al 1997) proposed that only three scales are sufficient to achieve good tonal rendition and dynamic range compression. Standard deviations of 15, 80 and 250 for the scales are used to enhance images under a mega pixel in size (Jonson et al 1997). 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 (D.J.Jobson 1997).

4.5 RESULTS AND DISCUSSION

Three images are selected to demonstrate the performance of Adaptive Multiscale retinex algorithm (girl, building and industry). 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 4.2 Girl input image

Figure 4.3(a) Different tiles of the girl image
Figure 4.3 (b) Different tiles of the girl image (9 Nos.)

The next step in this method is to find the minimum intensity for each tile and obtained value is assigned as $\beta$. The maximum intensity of each tile is obtained and assigned as $\alpha$. For our example, the minimum intensity of each tile is given in the below table.
Table 4.1 Minimum, maximum and difference intensity for each tile

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

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

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

(4.9)

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 new 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 new values of maximum and minimum intensity values of all the tiles of an image.

<table>
<thead>
<tr>
<th>Tiles</th>
<th>Minimum Intensity (( \beta ))</th>
<th>Maximum Intensity (( \alpha ))</th>
<th>Difference in Intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tile (1)</td>
<td>67</td>
<td>206</td>
<td>139</td>
</tr>
<tr>
<td>Tile (2)</td>
<td>73</td>
<td>211</td>
<td>138</td>
</tr>
<tr>
<td>Tile (3)</td>
<td>87</td>
<td>255</td>
<td>168</td>
</tr>
<tr>
<td>Tile (4)</td>
<td>62</td>
<td>255</td>
<td>193</td>
</tr>
<tr>
<td>Tile (5)</td>
<td>67</td>
<td>241</td>
<td>174</td>
</tr>
<tr>
<td>Tile (6)</td>
<td>68</td>
<td>207</td>
<td>139</td>
</tr>
<tr>
<td>Tile (7)</td>
<td>55</td>
<td>190</td>
<td>135</td>
</tr>
<tr>
<td>Tile (8)</td>
<td>59</td>
<td>207</td>
<td>148</td>
</tr>
<tr>
<td>Tile (9)</td>
<td>69</td>
<td>224</td>
<td>155</td>
</tr>
</tbody>
</table>
The global $\alpha$ and $\beta$ values are calculated just by finding the average of minimum and maximum intensity values of all the tiles. For the above example, the global $\alpha$ and $\beta$ values are 67.44 and 221.77 respectively. These values are applied to the expanded $\alpha$ and $\beta$ values to normalize the image. Below is the normalized image tiles after normalization using the above two values.

Figure 4.4 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 4.5 (a) Blending of tiles to form sub image-1

Figure 4.5 (b) Blending of tiles to form sub image-2
Figure 4.5 (c) Blending of tiles to form sub image-3

Figure 4.6 Blended output image
The above procedure is repeated for the remaining two images viz. building and industry.
Figure 4.8 Tiles of building input image
The minimum intensity for each tile, maximum intensity of each tile, the
differences between them and global and their expanded intensity values are calculated
and output images are blended. The enhanced images are presented below:

![Figure 4.9a Input Image (Girl)](image1)

![Figure 4.9b Output Image (Girl)](image2)

![Figure 4.10a Input Image (Industry)](image3)

![Figure 4.10b Output Image (Industry)](image4)
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 4.3 PSNR values using various methods**

<table>
<thead>
<tr>
<th></th>
<th>Modified CLAHE</th>
<th>Single Scale Retinex</th>
<th>Multi Scale Retinex</th>
<th>Improved Adaptive Multi Scale Retinex</th>
</tr>
</thead>
<tbody>
<tr>
<td>Girl</td>
<td>24.01</td>
<td>22.78</td>
<td>25.06</td>
<td>27.83</td>
</tr>
<tr>
<td>Industry</td>
<td>18.99</td>
<td>16.54</td>
<td>21.64</td>
<td>22.67</td>
</tr>
<tr>
<td>Building</td>
<td>19.34</td>
<td>17.09</td>
<td>19.98</td>
<td>20.45</td>
</tr>
</tbody>
</table>
The PSNR values of this method are compared with traditional single scale retinex method, multi scale retinex and modified CLAHE which we discussed in chapter 3. There is great improvement in PSNR values of girl image and industry image. Single scale retinex method produces low PSNR value when compared to modified CLAHE method. The PSNR value of improved adaptive multi scale retinex method for building image is not significant. This is due to domination of one color in the input image.
4.6 SUMMARY

In this work, 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 which we proposed in Chapter 3. 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.