Medical Image Enhancement using Multi Scale Retinex Algorithm with Gaussian and Laplacian surround functions

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Abstract-In order to improve medical image visual quality, this paper presents a multiscale retinex algorithm for medical image enhancement. This method adopts HSV color space, because HSV color space separates color from intensity. To achieve enhancement of medical image, down sampling original image into five versions namely, tiny scale, small scale, medium scale, fine scale, and normal scale. Later, applying contrast stretching and multi scale retinex (MSR) techniques in order to enhance the scaled versions of the image. Finally, to obtain the composite enhanced image, image is reconstructed by combining each of these scales in an efficient way. MSR can be considered as weighted sum of several single scale retinex (SSR) outputs. Reconstructed image highlights the details, reduces image noise and improves the overall contrast which is useful for diagnosis.

Keywords: Multiscale retinex, Single scale retinex, Medical image enhancement, RGB, HSV, Surround functions.

I. INTRODUCTION

Image enhancement plays a fundamental role in image processing where human experts gain an important decision based on the imaging information. The purpose of an image enhancement algorithm is to reconstruct the recorded image similar to that of the true picture. Medical image enhancement is one of the key research fields for the researchers due to extensive use of medical images in the diagnosis of various lesions. Medical image enhancement technologies have fascinated much attention since advanced medical equipments were put into use in the medical field. Enhanced images are preferred by a surgeon to assist diagnosis and interpretation because medical image qualities are often deteriorated by noise during acquiring and illumination condition. With the rapid increase in the usage and applications of medical images, it has become a compulsion to develop tools and algorithms for medical image processing.

A human observer can easily see individual objects both in the sunlight and shadowed areas, since the eye locally adapts while scanning the different regions of the scene. When attempting to display the image on a display, either the low intensity areas are underexposed and look black or the high intensity areas are overexposed and cannot be seen. Images taken from digital cameras suffer from a loss in clarity of details and color as it depends on the illuminance which in turn varies with distance from source. This problem of Color Constancy in images is solved using the basis of Retinex Theory. The Retinex takes an input digital image I and produces an output image R on a pixel by pixel basis. Types of retinex are single scale retinex and multi scale retinex algorithms.

Main goal of medical image enhancement is to provide clinician with enhanced contrast of local features, removes noise and other artifacts, enhanced edges and boundaries.

II. RELATED WORK AND CONTRIBUTIONS

Smriti Sahu et al. proposed comparative analysis of image enhancement techniques. Three types of liver ultrasound images used are normal, benign and malignant liver images. The techniques, which are compared on the basis of two evaluation parameters Peak Signal to Noise Ratio (PSNR) and Mean square Error (MSE).

Various image enhancement techniques have been applied like Contrast Stretching, Shock Filter, Histogram Equalization, Contrast Limited Adaptive Histogram Equalization (CLAHE),for the analysis of ultrasound liver image and comparison has been done and by comparison they showed that Shock filter gives the minimum MSE, highest PSNR value and it has given better performance than other techniques.[1]

Ankit Agarwal et al. Proposed a method which includes weighted average of the histogram equalized, gamma corrected and the original image are combined to obtain the enhanced processed image. This method starts with the image acquisition, this image is converted into gray image then the histogram equalized image is obtained and then the proposed gamma corrected image is obtained and at last the three images that are the original image, histogram equalized image and the gamma
corrected image are combined with weighted function to obtain enhanced image.

Two quantitative objective measures are used in his paper. Absolute Mean Brightness Error (AMBE) and the discrete entropy. They showed that proposed algorithm has achieved a higher discrete entropy value and the smaller AMBE value, indicating that proposed method enhances the contrast of the image while preserving the brightness level [2].

K.P. Indira et al. developed an algorithm for medical image enhancement in two steps. The first step corrects contrast of an image and in the second step wavelet fusion has been applied for medical image enhancement. The restored images were generally not satisfactory since the two steps adapted in this method over enhances the image. Therefore, this approach may not be suitable for medical image enhancement.[3]

Komal Vij et al. presented three histogram processing techniques, Histogram Equalization, Brightness Preserving Bi Histogram Equalization, Contrast Limited Adaptive Histogram Equalization (CLAHE). Histogram Equalization is a technique that generates a gray map which changes the histogram of an image and redistributing all pixels values to be as close as possible to a user specified desired histogram. HE allows for areas of lower local contrast to gain a higher contrast. Histogram equalization automatically determines a transformation function seeking to produce an output image with a uniform Histogram.

The Brightness preserving bi histogram equalization is another image enhancement technique which firstly decomposes an input image into two sub images based on the mean of the input image. Then the BBHE equalizes the sub images independently based on their respective histograms with the constraint that the samples in the formal set are mapped into the range from the minimum gray level to the input mean. Means one of the sub images is equalized over the range up to the mean and the other sub image is equalized over the range. From the mean based on the respective histograms, the resulting equalized sub images are bounded by each other around the input mean, which has an effect of preserving mean brightness.

Contrast limited adaptive histogram equalization operates on small regions in the image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. Among these three techniques authors have showed that BBHE (Brightness Preserving Bi-Histogram Equalization Technique) has the lowest MSE and highest PSNR. [4]

Md. Foisal Hossain et al. proposed a new method of medical image enhancement that improves the visual quality of digital images as well as images that exhibits dark shadows due to limited dynamic range of imaging. Non linear image enhancement technique is used in transform domain by the way of transform coefficient histogram matching to enhance image. Processing includes global dynamic range correction and local contrast enhancement which is able to enhance the luminance in the dark shadows keeping the overall tonality consistent with that of the input image. Logarithmic transform histogram matching is used which uses the fact that the relation between stimulus and perception is logarithmic. This proposed method of medical image enhancement based upon non-linear technique and the logarithmic transform coefficient histogram equalization improves the visual quality of images that contain dark shadows due to limited dynamic range of images [5].

### III. PROPOSED SYSTEM

The block diagram for the proposed system helps in reducing the image noise and improves the overall contrast and also enhances the edges. Block diagram for proposed system is shown in the fig 3.1.

![Block diagram of the proposed system](image)

**Fig 3.1:** Block diagram of the proposed system

Taking input medical image from data base and converting RGB to HSV form. Among HSV, we have taken only Value(V) channel for further process. Then down sampling value channel into five versions namely tiny, small, medium, fine, normal scales. Later, on each scaled versions, applying contrast stretching and MSR methods. To reconstruct the image, up sampling has been done. Finally to obtain enhanced image, HSV channels are combined and converting HSV to RGB form. Explanation of each block is explained below.

### A. RGB TO HSV CONVERSION

Below formula shows conversion of RGB to HSV.

\[
M = \max(r, g, b) \\
m = \min(r, g, b) \\
c = M - m \\
v = M \\
s = c / v
\]
In the above formula, the meaning of the variables are

M - the RGB component with the greatest value.
m - the RGB component with the smallest value

\text{c} - \text{chroma}

\text{r,g,b} - the components of the RGB model (red, green, blue)

\text{h,s,v} - the components of HSV model (hue, saturation, value)

**B. DOWNSAMPLING**

Downsampling is used to get the low resolution image from high resolution image.

**Downsampling by averaging method:**

Consider the low resolution image \(g(i,j)\) which is having the size of \(mxn\) where \(i=1,2,3,\ldots,m\) and \(j=1,2,3,\ldots,n\) are the low resolution intensity values. For a downsampling factor of ‘q’, the high resolution image \(f(k,l)\) will be of size \(qmxqn\). The forward process of obtaining \(g(i,j)\) from \(f(k,l)\) is given by

\[
g(i,j) = \frac{1}{4} \sum_{k=qi-1}^{qi} \sum_{l=qj-1}^{qj} f(k,l)
\]

Where ‘q’ is downsampling factor.

**Ex:** Let us consider an example of downsampling of 4x4 matrix into 2x2 matrix by averaging with downsampling factor of 2:

\[
f(k,l) = \begin{bmatrix}
1 & 1 & 2 & 1 \\
1 & 2 & 1 & 1 \\
1 & 1 & 1 & 1 \\
1 & 2 & 2 & 2 \\
\end{bmatrix}
= \begin{bmatrix}
1 & 1 \\
2 & 2 \\
\end{bmatrix}
\]

**C. CONTRAST STRETCHING**

Low contrast images occur due to poor or non-uniform lighting conditions so by stretching the pixel intensity values we can obtain high contrast image. Fig 3.2 shows typical contrast stretching transformations, which can be expressed as

\[
y = \begin{cases}
\alpha x & 0 \leq x < a \\
\beta (x-a) + y_a & a \leq x < b \\
\gamma (x-b) + y_b & b \leq x < L \\
\end{cases}
\]

D. MULTI SCALE RETINEX

Multi scale Retinex method can be implemented by using several single scale retinex outputs. Flow structure for single scale Retinex method is shown in the Fig.3.3

In this work, we have used 2 surround functions, Gaussian surround function and Laplacian surround function.

Equation for Gaussian surround function is given by Eqn(3)

\[
Gn(x,y) = Kn \ast e^{-x^2+y^2/2\sigma^2}
\]

Where \(Kn\) is...
Where x and y signifies the spatial coordinates, M and N represents the image size, σ is the Gaussian surround space constant, that is referred to as the scale of the SSR.

Equation for Laplacian surround function is given by Eqn(5)

$$L_n(x, y) = \frac{1}{4\sigma^2} e^{-\frac{(u-x)^2 + (v-y)^2}{2\sigma^2}}$$  \hspace{1cm} (5)

In Eqn(5), x and y are spatial coordinates, u is mean, σ is Laplacian surround space constant.

Multi scale retinex method is considered as extended single scale retinex method. Flow structure for multi scale retinex method is shown in the Fig.3.4

MSR output is weighted sum of several different SSR outputs and it is represented in Equation (6).

$$MSR(x,y) = \sum_{n=1}^{N} W_n \cdot SSR(x,y)$$  \hspace{1cm} (6)

where MSR(x,y) is MSR output, Wn is weighting factor which has value between 0 to 1 and N indicates number of scale(N=3). SSR(x,y) is output of single scale retinex method.

In Fig.3.4, S1,S2,S3 are surround functions(Gaussian surround function or Laplacian surround function) which acts as low pass filters.SSR1(x,y), SSR2(x,y), SSR3(x,y) are three SSR outputs, which are multiplied with weighing factors and all three SSR outputs are added to obtain MSR output.

D. UP SAMPLING

Up sampling is used to get the high resolution image from low resolution image.

Up sampling by replication method

The principle of replication is ‘for every pixel of the image, put the same value of the pixel in a grid of MxN pixels’. The result obtained will be of 2Mx2N pixels.

Example is shown below.

$$\begin{bmatrix}
1 & 2 \\
3 & 1
\end{bmatrix} \rightarrow \text{Replicate rows} \rightarrow \begin{bmatrix}
1 & 1 & 2 & 2 \\
1 & 1 & 2 & 2 \\
3 & 3 & 1 & 1 \\
3 & 3 & 1 & 1
\end{bmatrix}$$

E. HSV TO RGB CONVERSION

Below formula shows conversion of HSV to RGB.

$$c = v \cdot s$$

$$m = v - c$$

$$x = c \cdot \left(1 - \left|\frac{h}{60}\mod 2 - 1\right|\right)$$

$$r, g, b = \begin{cases}
(c + m, x + m, m), h \in [0, 60] \\
(x + m, c + m, m), h \in [60, 120] \\
(m, c + m, x + m), h \in [120, 180] \\
(x + m, m, c + m), h \in [180, 240] \\
(c + m, m, x + m), h \in [240, 300] \\
(m, m, m), \text{otherwise}
\end{cases}$$

In the above formula, The meaning of the variables are

m - the RGB component with the smallest value

c - chroma

r,g,b - the components of the RGB model (red, green, blue)

h,s,v - the components of HSV model (hue, saturation, value)

x - an intermediate value used for computing the RGB model.

IV. SYSTEM IMPLEMENTATION

The proposed system is implemented in GUI with the help of guide which is shown in Fig.4. The detailed description is explained below.
Here the reference image and low contrast image are selected from database. For multi-scale retinex, three space constants ($\sigma_1$=small scale, $\sigma_2$=medium scale, $\sigma_3$=large scale) which is considered as scale of the image and three weighting factors corresponding to each 3 space constants are considered. For single-scale retinex, only one space constant ($\sigma$=medium scale of MSR) and one weighting factor are considered. Output 1 is MSR output image using Gaussian surround function, output 2 is MSR output image using Laplacian surround function, output 3 is SSR output image using Gaussian surround function, output 4 is SSR output image using Laplacian surround function.

V. RESULTS

The experimental results for single-scale retinex and multi-scale retinex using Gaussian surround function and Laplacian surround function with different space constants are shown below.

A) Tabulation for PSNR values (SSR)

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Space constants ($\sigma$)</th>
<th>PSNR in dB (Gaussian) MSR</th>
<th>PSNR in dB (Laplacian) MSR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>15.6996</td>
<td>22.992</td>
</tr>
<tr>
<td>2</td>
<td>80</td>
<td>18.0665</td>
<td>26.5178</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>20.3876</td>
<td>30.524</td>
</tr>
<tr>
<td>4</td>
<td>130</td>
<td>24.7962</td>
<td>36.6212</td>
</tr>
<tr>
<td>5</td>
<td>150</td>
<td>28.8614</td>
<td>37.4245</td>
</tr>
</tbody>
</table>

B) Tabulation for PSNR values (MSR)

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Space constants ($\sigma$)</th>
<th>PSNR in dB (Gaussian) MSR</th>
<th>PSNR in dB (Laplacian) MSR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>30, 50, 90</td>
<td>15.6996</td>
<td>22.992</td>
</tr>
<tr>
<td>2</td>
<td>50, 80, 150</td>
<td>20.3876</td>
<td>30.524</td>
</tr>
<tr>
<td>3</td>
<td>60, 100, 160</td>
<td>22.6606</td>
<td>33.063</td>
</tr>
<tr>
<td>4</td>
<td>60, 130, 190</td>
<td>24.7962</td>
<td>36.6212</td>
</tr>
<tr>
<td>5</td>
<td>60, 150, 200</td>
<td>28.8614</td>
<td>37.4245</td>
</tr>
</tbody>
</table>

C) Graphical Analysis

The graphical analysis gives the performance analysis of the proposed system. The below graphs shows that, as the space constant increases the PSNR of the SSR & MSR increases.
VI. CONCLUSION

In this paper, Single scale retinex and multi scale Retinex methods using Gaussian and laplacian surround functions has been designed, implemented and tested on medical image with different surround space constants (σ) which can be used to enhance poor quality medical images and which is very useful in diagnosis purposes.

REFERENCE


