COMPARISON OF IMAGE ENHANCEMENT TECHNIQUES USING RETINEX MODELS

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Abstract - Image enhancement improves the quality of images for human viewing. There are often serious discrepancies existing between images and the direct observation of the real scenes. Human perception has natures of dynamic range compression and color rendition on the scenes. It can compute the details across a large range of spectral and lightness variations, thus it is color constant. Single-scale Retinex (SSR) was defined as an implementation of center/surround Retinex. Superposition of weighted different scale SSR balances both dynamic range compression and tonal rendition, which is Multiscale Retinex (MSR). For color images, spatial averages of the three color bands are far from equal, thus the output appears grey. To address this issue, a weight factor for different channels is introduced which is Multiscale Retinex with color restoration (MSRCR). In this paper, SSR, MSR and MSRCR systems for image enhancement are implemented and their performances are compared using MATLAB as the software tool.

Keywords— Dynamic range, color constant, Retinex, surround space constant, SSR, MSR, color restoration, MSRCR

I. INTRODUCTION

The human visual system is better than machines when processing images. Observed images of a real scene are processed based on brightness variations. The images captured by machines are easily affected by environmental lighting condition, which tends to reduce its dynamic range[1]. On the contrary, the human visual system can automatically compensate the image information by psychological mechanism of color constancy[2]. Color constancy, an approximation process of human perception system, makes the perceived color of a scene or objects remain relatively constant even with varying illumination conditions. Land [3] proposed a concept of the Retinex, formed from "retina" and "cortex", suggesting that both the eye and the brain are involved, to explain the color constancy processing of human visual systems. Although single-scale retinex (SSR) algorithm could support different dynamic-range compressions, the multi-scale retinex (MSR) can better approximate human visual processing by transforming recorded images into a rendering which is much closer to the human perception[4] of the original scene. MSR is good for gray images. But it could be a problem for the color images because it does not consider the relative intensity of color bands. This can be seen from MSR output which is the relative reflectance's[5] in the spatial domain. Considering the images out of gray world, whose average intensity for the three color bands are far from equal, the output pixel values of MSR for three channels will be more close, which makes it look more gray. The solution to this problem is MSRCR that introduces weights for three color channels depending on the relative intensity of the three channels in the original images. The paper is organized as follows. Section II deals with single scale retinex. Section III deals with multi-scale retinex. Section IV deals with multi-scale retinex with color restoration. Section V gives the implementation details. The paper is concluded in section VI.

II. SINGLE SCALE RETINEX

The basics of SSR include a logarithmic photoreceptor function that approximates the vision system based on a center/surround [6] function. The SSR is given by:

$$R_i(x,y) = \log_i(x,y) - \log[F(x,y) * \mathrm{I}_i(x,y)] \quad (1)$$

where I_i (x,y) is image distribution in the ith color band, F(x,y) is the normalized surround function[7] such that:

$$\iint F(x,y)dxdy = 1 \quad (2)$$

The purpose of the logarithmic manipulation is to transform a ratio at the pixel level to a mean value for a larger region. The general form of the center/surround retinex is similar to the Difference-of-Gaussian (DOG) function widely used in natural vision science to model both the receptive fields of individual neurons and perceptual processes. The only extensions required are i) to greatly enlarge and weaken the surround Gaussian (as determined by its space and amplitude constants) and ii) to include a logarithmic function to make subtractive inhibition into a shunting inhibition (i.e., arithmetic division). The surround space function computes the average of the surrounding pixel values and assigns it to the center pixel.

Land [3] proposed an inverse square spatial surround function:

$$F(x,y) = K * \exp(-\frac{r^2}{c^2}) \quad (3)$$

Moore suggested the exponential formula with absolute parameter:

$$F(x,y) = \exp(-r/c) \quad (4)$$

Hurlbert [8] suggested:

$$F(x,y) = K * \exp(-\frac{r^2}{c^2}) \quad (5)$$

For a given space constant, the inverse-square surround function accounted for a greater response from the neighboring pixels than the exponential and Gaussian functions. The spatial response of the exponential surround function was larger than that of the Gaussian function at distant pixels. Therefore, the inverse-square surround function was more commonly used in global dynamic range compression and the Gaussian surround function was generally used in regional dynamic range compression[9]. The exponential and Gaussian surround functions were able to produce good dynamic range compression over neighboring pixels. The selection of space constant is related with visual angle in the direct observation. But the value cannot be theoretically modeled and determined. Basically there is a trade-off between dynamic compression, (for example, details in the shadow) and color rendition.

SSR is incapable of simultaneously providing sufficient dynamic range compression and tonal rendition. It also introduces halos around the objects.

III. MULTI SCALE RETINEX

In order to preserve both the dynamic range compression and color rendition, Multi-scale retinex, which is a combination of weighted different scales of SSR [10], is a good solution:

$$R_{MSR_i} = \sum_{n=1}^{N} w_n R_{n_i} \quad (6)$$

where N is the number of the scales, R_{ni} is the ith component of the nth scale, w_n is the weight of the nth scale. For MSR, the number of scales needed, scale values and weight values are important. Experiments showed that three scales are enough for most of the images and the weights can be equal. Generally fixed scales of 15, 80 and 250 can be used, or scales of fixed portion of image size can be used. The weights can be adjusted to weigh more on dynamic range compression or color rendition [11]. The MSR based images have significant dynamic range compression in the boundary between the light parts and dark parts and reasonable color rendition in the whole image scale.

MSR combined various SSR weightings, selecting the number of scales used for the application and evaluating the number of scales that can be merged. Important issues to be concerned were the number of scales and scaling values in the surround function, and the weights in the MSR. The best weights had to be chosen in order to obtain suitable dynamic-range compression at the boundary between light and dark parts of the image, and to maximize the brightness rendition [12] over the entire image. MSR worked by compensating for lighting variations to approximate the human perception of a real scene. There were two methods to achieve this: (1) compare the psychophysical mechanisms between the human visual perceptions of a real scene and a captured image, and (2) compare the captured image with the measured reflectance values of the real scene.

Thus the method involved combining specific features of MSR with processes of SSR, in which the center/surround operation was a Gaussian function. The logarithm was then applied after surround function processing (i.e., two-dimensional spatial convolution). Next, appropriate gain and offset values were determined

according to the retinex output and the characteristics of the histogram. These values were constant for all the images. This procedure yielded the MSR function. However, it is difficult to predict whether the color of the reproduction will be accurate; and it has issues of color sensitivity [13].

IV. MULTI SCALE RETINEX WITH COLOR RESTORATION

To address the drawback of MSR with regard to color restoration, we introduced weights for three color channels depending on the relative intensity of the three channels in the original images. The relative intensity of three channels is given by:

$$I_i(x,y) = \frac{I_i(x,y)}{\sum_{j=1}^{s} I_i(x,y)} \qquad (7)$$

I_i is the ith band of the input image and S is the total number of color bands. The color restoration [14] is given by:

$$C_i(x,y) = f[I_i(x,\mathrm{y})] \qquad (8)$$

The best overall color restoration function is given by:

$$C_i(x,y) = \beta \log[\alpha I_i(x,y)] \qquad (9)$$

where β is the gain constant and α controls the strength of non-linearity.

The general form of the MSRCR can be summarized by the following equation:

$$I_i^{'}(x,y) = \frac{d_{\max}}{r_{\max} - r_{\min}} * (I_i(x,y) - r_{\min}) \qquad (10)$$

where i =1, ….. N, w_s is the weight of the scale, I_i is the ith band of the input image, and N is the number of bands in the input image. The surround function M_s is defined by:

$$M_s(x,y) = K\, exp[\sigma^2_s/(x^2 + y^2)] \qquad (11)$$

where σ_s is the standard deviation of the Sth surround function, and

$$\iint K\, exp[\sigma^2_s/(x^2 + y^2)]dx\, dy = 1 \qquad (12)$$

$$F_i(x,y) = G_f \log\left[\frac{I_i(x,y)}{\sum_{n=1}^{N} I_n(x,y)} - O_f\right] \qquad (13)$$

The G_f and O_f are color restoration factors defined as ***gain*** and ***offset*** respectively. The final gain and offset values are needed to scale the output of the 'log' domain operations to the (R, G, B) color space, and G_f and O_f control the degree to which the color restoration function *F(x,y)* affects the overall color of the output image. These constants, the number of scales, *S*, and the widths of the surround functions σ_s, are image independent in the sense that we apply the same (canonical) set of constants to every image that we process.

Some of the images processing related issues in MSRCR are:

- Negative Offset

This is an attempt to increase the dynamic range (i.e. visual contrast) provided by the device but is often photometrically incorrect and results in *false* zeroes. The effect of the MSRCR is to produce a harsher-than-normal contrast. A simple correction, i.e. application of a positive offset to the original image can mitigate this effect.

- Automatic Gain and Offset [15]

A negative offset is typically applied to map the minimum value to black and then a gain is applied to map the resultant maximum value to white. Care is taken to ensure that actual white exists in the scene. The MSRCR is very resilient to such adjustments. Since the difference between the MSRCR outputs in the original and the auto/gain case is insignificant, the result is not shown here.

- Positive Offset

Typically brightness in an image is increased by applying a positive offset, which often manifests itself as an overall haziness in the input image. Though the application of the MSRCR reduces this haziness, there is still a sense of haziness overall. Further alleviation of this effect can be achieved by reducing the final offset value; O_r from its canonical value.

In this paper, color problems were focused utilizing MSRCR as an image processing technique to solve the problems of the accuracy of the color of the reproduction. The main practical consequence of MSR is that it is not appropriate for applications which are sensitive to color.

The results of MSRCR prove that it is efficient to avoid graying out effects. It maintains good color rendition and color constancy.

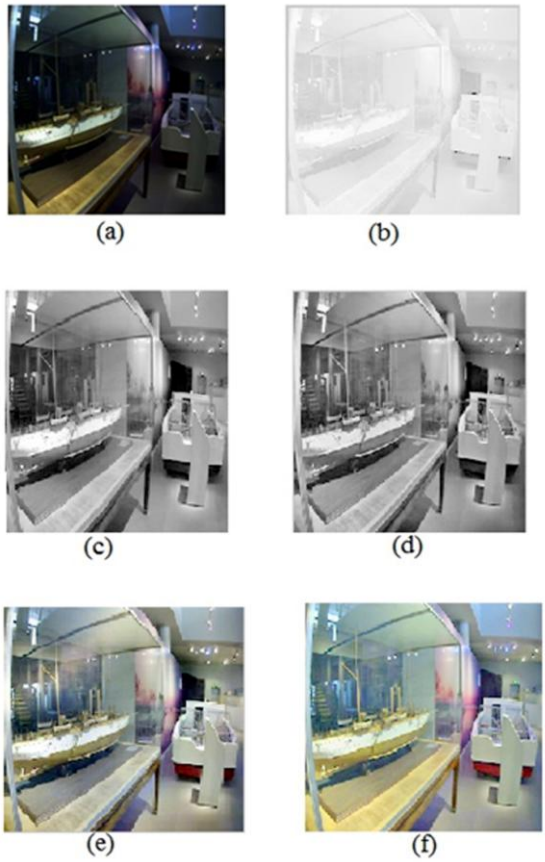

FIGURE 1 (A) INPUT (B) SSR AT SCALE 15 (C) SSR AT SCALE 80 (D) SSR AT SCALE 250.

Image (e) is the result of combining the results at these three scales and (f) is the result with the color restoration step added. Images (b), (c), (d), and (e) have been adjusted to have a brightness range similar to that of (f), as the MSR gain-offset constants are meant to apply to the complete process, as applied to get image (f). The result of the above processing will have both negative and positive RGB values and the histogram will typically have large tails.

Standard MSR typically does not brighten the shadow as much, but has much less of this edge effect, and the shadow simply looks like a less dark shadow. Again, as mentioned above, one of the reasons for this difference is that part of the dynamic range compression of standard MSR is due to the logarithm operation. This can be verified by applying the processing without any ratios. The observation that the logarithm operation has a definite benefit leads to the second method for luminance based MSR style processing.

Application of gain and offset is a linear operation and hence has limited success on scenes that encompass a much wider dynamic range than that can be displayed. In this case, loss of detail occurs due to saturation and clipping as well as due to poor visibility in the darker regions of the image. For a scene with dynamic range between r_{max} and r_{min}, and a display medium with dynamic range d_{max}, this transform can be represented by

$$I_i^{'}(x,y) = \frac{d_{\max}}{r_{\max} - r_{\min}} * (I_i(x,y) - r_{\min}) \qquad (14)$$

where I_i is the ith input band, and $I_i^{'}$ is the ith output band. This will transform the scene to completely fill the dynamic range of the display medium.

V. IMPLEMENTATION

SSR is performed on individual channels. Combining the weighted function of the SSR gives MSR image and restoring color information of each pixel gives an enhanced MSRCR color image. Fig.2 shows the

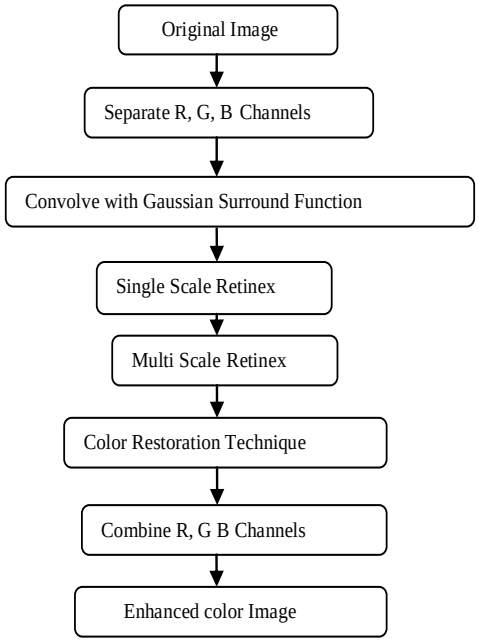

FIGURE .2: SEQUENCE OF IMPLEMENTATION

B. Simulation Results

By implementing the different techniques on the image a comparison is obtained and studied. The histograms depict the distribution of pixels and it can be seen that the pixel concentration is spread more evenly over the entire intensity range to provide a smooth and uniform appearance by the MSRCR algorithm.

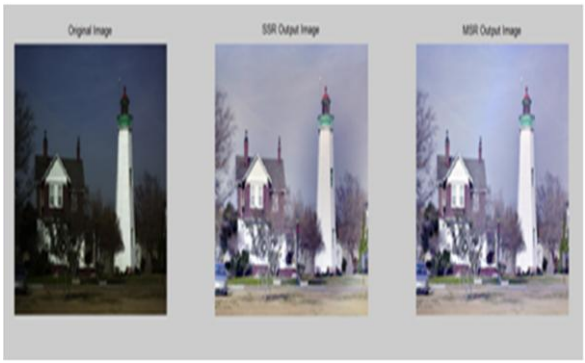

FIGURE.3: A) ORIGINAL IMAGE B) SSR OUTPUT C) MSR OUTPUT

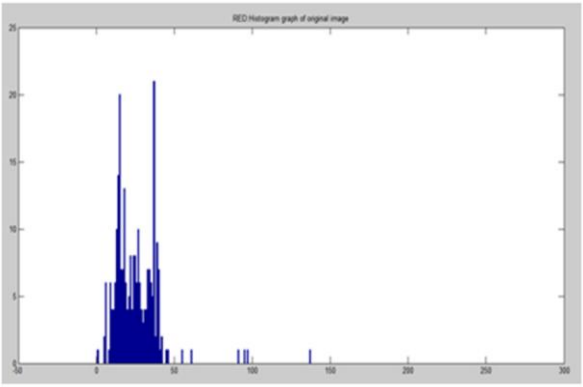

FIGURE .4: RED HISTOGRAM OF ORIGINAL IMAGE

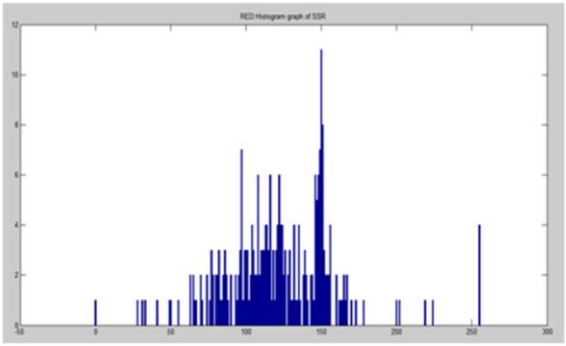

FIGURE .5: RED HISTOGRAM OF SSR

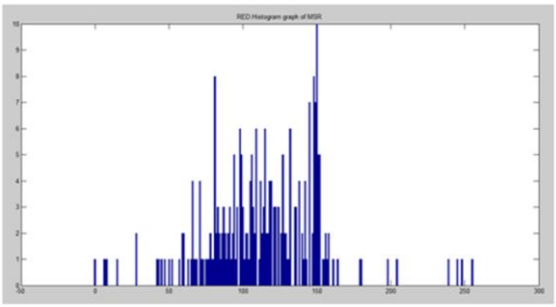

FIGURE.6: RED HISTOGRAM OF MSR

FIGURE .7: MSRCR OUTPUT IMAGE

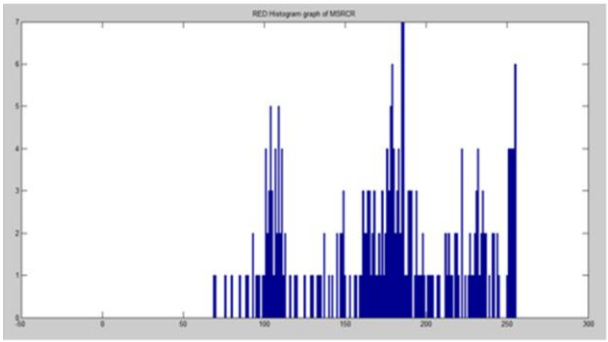

FIGURE .8: RED HISTOGRAM OF MSRCR

VI. CONCLUSION

In this paper, the implementation of Image Enhancement using MSRCR has been discussed. The implementation is used in the space research application for the space related analysis and security cameras in bank or other places where image analysis is done to pinpoint the object accurately. In the medical field, X-Ray and CT scan images are enhanced using retinex techniques to increase clarity of the tissues. So, this implementation will be very helpful for the space researchers, doctors and security people around any campus. The future scope of this paper is to implement the Retinex based algorithms on the DSP processor based hardware; to enhance the performance of the system, adaptive Retinex based systems can be implemented.

Retinex based Image Enhancement Systems using wavelet decomposition can be considered as a future work of the system.

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