Enhancement and Correction of Medical Images Using Multiscale Retinex

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Abstract: ***The Retinex is an image enrichment algorithm that improves the brightness, contrast and sharpness of an image. A new method for enhancing the contrast of inhomogeneous images by retinex algorithm is proposed. It can correct the blurring in deep anatomical structures and in homogeneity. Multi scale retinex (MSR) employed SSR with different weightings to correct in homogeneities and enhance the contrast of images". Its performance was also compared with other methods based on two indices: (1) the peak signal-to-noise ratio (PSNR) and (2) the contrast-to-noise ratio (CNR).***

Keywords: Retinex, PSNR, CNR

1. Introduction

The Retinex model for the computation of lightness was introduced by Land and McCann.1 McCann refers to these models as ratio-product-reset average, but for simplicity, we call these operations the Retinex model. Frankle and McCann provide complete FORTRAN code for their algorithm, with extensive discussion of image processing steps that follow spatial comparisons. Since that time, Land and his colleagues have described several variants on the original method. 2–6 the variants on Retinex mainly aim to improve the computational efficiency of the model, while preserving its basic underlying principles. Retinex calculations aim to predict the sensory response of lightness. Stretching the pixel dynamic range of certain objects in an image is a widely adopted approach for enhancing the contrast [2]. The image contrast-enhancement techniques can be divided into two types: global and local histogram enhancement [7, 8]. The (global) histogram equalization technique improved the uniformity of the intensity distribution of an image [5, 6] by equalizing the number of pixels at each gray level. The disadvantage of this method is that it is not effective in improving poor localized contrasts [8]. Local histogram enhancement [4, 5] used an equalization method to improve the detailed histogram distribution within small regions of an image, and also preserved the gray-level values of the image. The obtained histogram is updated in neighboring regions at each iteration, and then local histogram equalization is applied. However, the visual perception quality of a processed image is subjective, and it is known that both global and local histogram equalization do not result in the best contrast enhancement.

2. Method

2.1 Retinex Algorithm

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 lightening conditions, which tends to

2.2 Multi-Scale Retinex

It was our intention to select the best value of scale factor c in the surround function F(x, y) It was our intention to select the best value of scale factor *c* in the surround function *F*(*x*, *y*) based on the dynamic-range compression and brightness rendition for every SSR. We also intended to maximize the optimization of the dynamic-range compression and brightness rendition. MSR was a good method for summing a weighted SSR

Single scale retinex for any pixel p(x, y) can be given by the equation:

$$R_i(x, y) = \log I_i(x, y) - \log[F(x, y) * I_i(x, y)], \quad i = 1, \dots, S, \quad \text{---Eq (1)}$$

Where, I(x, y) is an input image, R(x, y) is an output image and F(x, y) is normalized surrounding function and it is given by:

$F(x, y) = k \times e{-}(x^2 + y^2) / c^2$ -- Eq (2)

Multi scale retinex can be given by the equation [9]:

$$R_i(x, y) = \sum_{n=1}^{N} w_n R_{ni}, \quad i = 1, \dots, S, \quad \text{--- Eq (3)}$$

Where, R_{ni} can be given by following equation

$$R_{ni}(x, y) = \log I_i(x, y) - \log[F_n(x, y) * I_i(x, y)] \quad \text{-Eq (4)}$$

Finally, equation can be representing as:

$$R_i(x, y) = \sum_{n=1}^{N} w_n (\log I_i(x, y) - \log(F_n(x, y) * I_i(x, y)), \quad i = 1, \dots, S, \quad \text{-Eq (5)}$$

Where, *N* represented a scaling parameter, *ni R* represented the *I* th component of the *n*th scale, *MSRi R* was the *n*th spectral component of the MSR output, and *n* w represented the multiplication weight for the *n*th scale. The differences between *R*(*x*, *y*) and *R* (*x*, *y*) *n* resulted in surround function *F* (*x*, *y*).

$F(x, y) = k \times e{-}(x^2 + y^2) / c^2$ --- Eq (6)

The Multiscale algorithm is a tone reproduction operator. The algorithm estimates scene reflectance's from the ratios of scene intensities to their local intensity averages. First, the scene is decomposed into a set of images that represent the mean of the image at different spatial resolutions by applying Gaussian filters of different sizes. Next, a set of images that measure the scene reflectance is produced by dividing the original picture point wise by the decomposed pictures. Then, a log function is applied to each of the images to reduce the image dynamic range. Finally, the displayed image is reconstructed by adding the compressed images together. The equation that describes the Single Scale Retinex is: *Single Scale Retinex (SSR)*

$$R(x, y) = \log I(x, y) - \log [F(x, y)*I(x, y)] \text{ -- Eq (7)}$$

Where I(x, y) is the image intensity, "*" is the convolution operator and F(x, y) is the surrounding function:

$$F(x, y) = k \times e{-}(x2 + y^2) / c^2 \text{ ----Eq (8)}$$

Where c is the Gaussian shaped surrounding space constant and k is selected such that:
The equation that describes the Multi Scale Retinex is: *Multi Scale Retinex (MSR):* (3) where, Rn(x, y) are different scale SSR (obtained with different Gaussian functions) and wn is the weight of each SSR. Usually, these weights are taken to be equal.

2.3 Peak signal-to-noise ratio (PSNR) and (2) the contrast-to-noise ratio (CNR)

Obtaining images of the highest possible clarity is crucial to effective structural brain imaging. The quality of images obtained from histogram equalization, local histogram equalization, the wavelet-based algorithm, and retinex can be quantified using appropriate indices. The values of PSNR and CNR for the phantom images obtained in the present study with the four correction methods where higher values indicate images of higher quality, the use of SSR increased PSNR but decreased CNR. The general effect of retinex processing on images with regional or global gray-world violations is a "graying out" of the image, either globally or in specific regions.

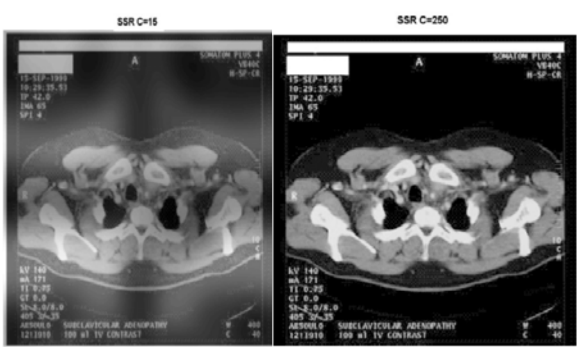

Figure1: Figure showing SSR and MSR effect

This de saturation of color can, in some cases, be severe. More rarely, the gray-world violations can simply produce an unexpected color distortion. Therefore, we consider a color restoration scheme that provides good color rendition for images that contain gray-world violations. We, of course, require the restoration to preserve a reasonable degree of color consistency, since that is one of the prime objectives of the retinex. Color constancy is known to be imperfect in human visual perception, so some level of illuminant color dependency is acceptable, provided it is much lower than the physical spectrophotometric variations. In order to illustrate the performance of different transformations applicable to MR scene sequences, we have used simulated and acquired MRI sequences. Each sequence consists of four T2-weighted and one T1-weighted MR images. Simulations were performed on a Vicom image processing computer. Acquired MRI sequences of an egg phantom, an a arose phantom, and a human brain were acquired on a 1.5 T General Electric Signal MRI system.influence absence within the period T_{req} after the last diagnostic, i.e. in the last remainder.

3. Results

3.1 Phantom Image

The performance of our retinex algorithm was assessed by determining the parameters for a test series of MR images of the phantom, with dimensions of 256 × 256 pixels and 16-bit quantization. The dynamic-range compression and brightness constancy were determined in the MR images of the test series, based on post processing by the retinex method.

Fig. 2 showed the results of using SSR and MSR to correct for the in homogeneity of an MR image of the phantom. The original MR image was shown in Fig. 2(a), which exhibited in homogeneity, no uniformity, low brightness, and a large dynamic range. SSR with a scale of every 10 pixels between 0 and 255 was used to analyze the series of phantom images. SSR with a scale of 15 pixels was also applied in this test. Fig. 2(b), (c), and (d) illustrated the successful reductions in intensity in homogeneity of the phantom images using SSR with scales of 15, 80, and 250 pixels respectively. The images in Fig. 2(b), (c), and (d) showed dynamic-range compressions and brightness were large, moderate, and small, respectively, which indicated the dynamic-range compression increased when the SSR scale decreased. Fig. 2(e) showed the image obtained from MSR by combining three scales of SSR weightings (ω_n = 1/3, n = 1, 2, and 3), where the three scales of SSR were 15, 80, and 250 pixels as used by Jobson et al [33, 34]. The images obtained from the retinex algorithms were of higher quality than the original phantom image. Also, Fig. 2(f) showed an MR image captured by a volume coil as a receiver with the same MR imaging procedures and parameters. Comparison of Fig. 2(e) and (f) revealed that MSR successfully corrected the original MR phantom image.

a. Original MSR b**.** Result MSR

Figure 2: Original MSR & Result MSR

Animal Image

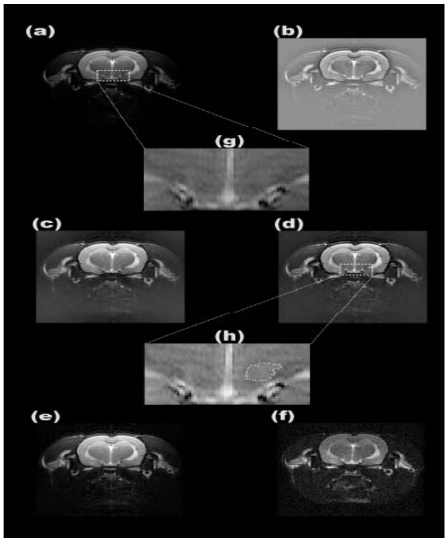

Figure 3: Result of SSR and MSR

In Fig. 3, results of applying SSR and MSR to adjust a rat brain MR image were shown. Fig. 3(a) showed the original MR image, which was one of 28 coronal brain slices. Fig. 3(b), (c), and (e) showed the images obtained from SSR with scales of 15, 80, and 250 pixels respectively, with dynamic-range compressions that are large, moderate, and small; and brightness variations that are small, moderate, and large respectively. The images obtained from retinex demonstrated better visual rendition than that of the original MR image in Fig. 3(a). The background of the original brain MR image was blurred**,** and its brightness contrast and dynamic range were poor. Fig. 3(d) was the image obtained from MSR, displaying its strength of combining small, moderate, and large scales of SSR with the same weightings of *n*w = 1/3 (*n* = 1, 2, and 3). Fig. 3(f) showed an MR image captured by a volume coil with the same MR imaging procedure, it had better homogeneity than the image obtained by surface coils, yet the resolution was lower, the details in the medial forebrain bundle (MFB) and mammillothalamic tract (MT) regions were not clear and inhomogeneous. Fig. 3(h) showed the MR image enlarged (× 5) from dotted-line block of Fig. 3(d) from MSR, regions (MFB and MT) circled with dotted-curve demonstrated better homogeneity and clarity. Fig.3 (h) exhibited clearer deep anatomical structures from MSR than Fig. 3(g) from original image. The MSR clearly improved the quality, relative to that of the original MR image. Comparing among the original MR image, the image captured by a volume coil and the image obtained from the retinex algorithm revealed that the last method showed the best performance in terms of brightness, dynamic-range compression, and over all visual renditions.

4. Conclusion

The MSR, comprised of three scales (small, intermediate, and large), was found to synthesize dynamic range compression, color consistency, and tonal rendition, and to produce results that compare favorably with human visual perception, except for scenes that contain violations of the gray-world assumption. Even when the gray-world violations were not dramatic, some desaturation of color was found to occur. A color restoration scheme was defined that produced good color rendition even for severe gray-world violations, but at the expense of a slight sacrifice in color consistency. In retrospect, the form of the color restoration is a virtual spectral analog to the spatial processing of the retinex. This may reflect some underlying principle at work in the neural computations of consciousness; perhaps, even that the visual representation of lightness, color, and detail is a highly compressed mesh of contextual relationships, a world of relativity and relatedness that is more often associated with higher levels of visual processing such as form analysis and pattern recognition. While there is no firm theoretical or mathematical basis for proving the generality of this color restored MSR, we have tested it successfully on numerous diverse scenes and images, including some known to contain severe gray-world violations. No pathologies have yet been observed. Our tests were, however, confined to the conventional 8-b dynamic range images, and we expect that some refinements may be necessary when the wider dynamic range world of 10–12-bimages is engaged.

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