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Ameliorating the Dynamic Range of Magnetic Resonance Images Using a Tuned Single-Scale Retinex Algorithm

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Abstract

Magnetic Resonance (MR) images provide physicians with vital information about different diseases of the human body. Thus, such images must have adequate clarity to become highly beneficial in the medical field. However, it is known that MR images have a poor dynamic range which significantly affects their visible quality due to the deficient brightness and contrast. In order to deliver evident results, a tuned single-scale Retinex algorithm is utilized in this study to ameliorate the dynamic range which eventually results in better brightness and contrast. The obtained results are compared with various algorithms that utilize contemporary, complex and renowned concepts. Moreover, many naturally-degraded MR images are used for experimental and comparable purposes. Finally, intensive experiments revealed the favorability of the adopted algorithm, in that it produced evident results without any visible flaws and outperformed the comparable algorithms in terms of visible quality.

Keywords: *Magnetic resonance images, Poor dynamic range, Tuned retinex algorithm, Medical image enhancement*

1. Introduction

Magnetic Resonance (MR) imaging is a valuable diagnostic tool in the field of radiological imaging, as it is utilized for obtaining cross-sectional images of the human body [1]. Although such modality provides important medical information, its images must be interpreted by specialists. Hence, if the visible quality of such images is low, it would be difficult to the specialist to extract useful information or provide accurate diagnosis for many diseases [2]. Even further, obtaining high quality MR images remains a challenging problem due to the presence of various types of image degradations [3]. Generally, the capturing technology of optical images has a limitation which is labeled as low dynamic range. Such limitation can cause saturation for some image details while obscuring other details in the darkness. In MR images, the deficient brightness and contrast are common degradations, in which they severely affect its visible quality [4]. Such degradations occur due to numerous real-world restrictions. These degradations are also recognized as dynamic range limitation, which is a well-known problem in the field of digital image processing. Hence, MR images are labeled as poor dynamic range images [5]. To address this issue, many research works have been proposed to make the latent details of MR image observed naturally by the human eye, in which the proposed methods vary from simple to complex depending on the used processing notion. The enhancement techniques of digital image processing are often used to improve the brightness and contrast of degraded MR images, in which they can help dramatically in facilitating

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accurate diagnosis of diseases. There are a number of methods that can be used to process the poor dynamic range artifact such as, Eigen filters [6], linear filters [7-8], contrast limited adaptive histogram equalization [9], multiscale edge representation [10], multiscale retinex [11], type II fuzzy set [12], linear combinations based algorithm [13], hierarchical correlation histogram analysis [2], optimum wavelet based masking [14], and many more. Although numerous methods have been proposed by various researchers to overcome the aforementioned limitation, the door is still wide open for new methods due to the existence of wide variety of challenges regarding this domain of science. Therefore, it is necessary to ameliorate the brightness and adjust the contrast while preserving fine details of MR images, so that such important details would become significantly apparent. Hence, in this article, the authors have attempted to deal with the aforesaid limitation by using a tuned version of the renowned single-scale retinex algorithm, because the retinex theory was designed to describe the human visual perception. Accordingly, this study is aimed to use an abridged version of the proposed algorithm in [15] with MR images because of its efficiency and rapidity in improving the dynamic range, which eventually provides better brightness and contrast for the processed images. Despite the simplicity of the adopted algorithm, it has not been explored with MR images according to the best of our knowledge. The remaining sections of this article are structured as follows. In Section 2, the used algorithm is described in details. In Section 3, the empirical results are discussed comprehensively. Finally, vital conclusions are given in Section 4.

2. Tuned Single-Scale Retinex Algorithm

The retinex theory was originally introduced to describe the human visual perception [16]. Based on this theory, various competent image enhancement methods have been proposed [17]. In [15], a novel algorithm that utilizes the retinex theory was developed to improve the contrast of computed tomography (CT) medical images. Accordingly, this ameliorated version of the standard single-scale retinex algorithm can process the contrast of a given CT image while preserving its brightness from being altered. It is known that the contrast of CT images is quite low, yet their brightness is somehow acceptable. However, the brightness and contrast of MR images are relatively low in many situations. Therefore, only the tuned portion of [15] is adopted in this study to process the poor brightness and contrast of MR images. The tuned single-scale retinex (TSSR) algorithm can be simply described as follows:

$$F(x,y) = \frac{N * e^{-\frac{\left(H^2+V^2\right)}{(R*C)^2}}}{\lambda} \tag{1}$$

$$N = \frac{1}{\sum_{j=1}^{M}\sum_{k=1}^{N} e^{-\frac{\left(H^2+V^2\right)}{(R*C)^2}}} \tag{2}$$

$$R_{TSSR}(x,y) = \log\left[I(x,y)\right] - \log\left[F(x,y) \otimes I(x,y)\right] \tag{3}$$

Where, $F(x, y)$ denotes the output of the modified Gaussian surround function, N represents a normalization factor, H and V are two matrices that the sizes of which are similar to the processed image, wherein they signify the horizontal and vertical grayscale gradients, R and C represent the image dimensions, x and y represent the spatial coordinates, $R_{TSSR}(x, y)$ denotes the output of the adopted algorithm, $I(x, y)$ represents the original degraded image, $\otimes$ symbolizes a convolution process and λ signifies a tuning parameter, wherein its value fulfills $\lambda > 0$. The value of λ controls the enhancement of the adopted algorithm, in which higher values can increase the brightness and change the contrast of the processed image.

3. Results and Discussion

In this section, the necessary computer experiments, related preparations, results and discussions are reported. To perform credible experiments and to assess the applicability of TSSR algorithm with MR images, only naturally-degraded images were used for experimental and comparable purposes.

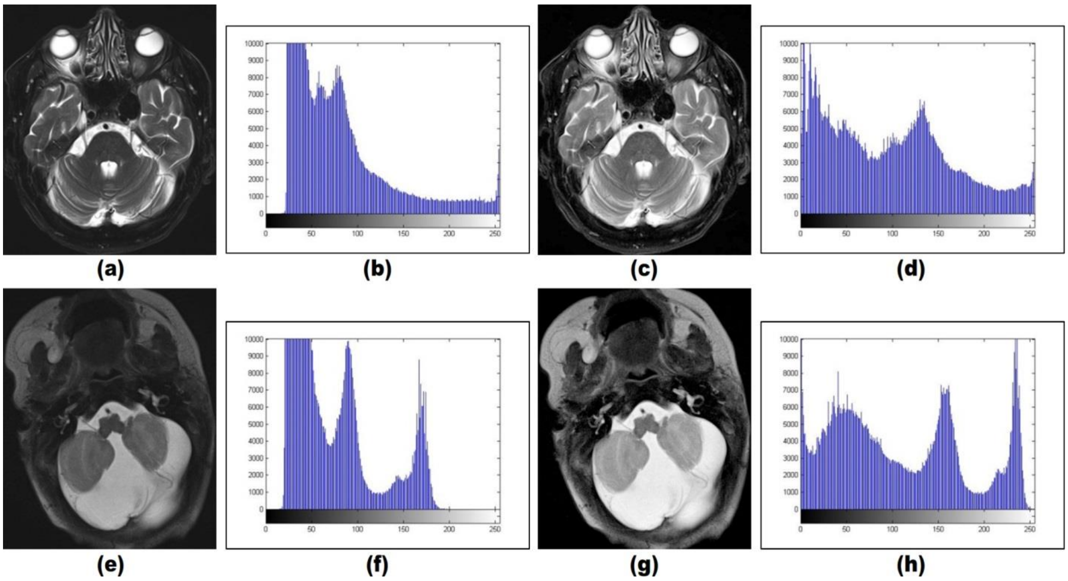

Figure 1. Processing Naturally-Degraded Brain MR Images: (a,e) are Real-Degraded Images; (b,f) are the Histograms of (a,e), Respectively; (c,g) are the Results of the Tuned Single-Scale Retinex; (d,h) are the Histograms of (c,g), Respectively

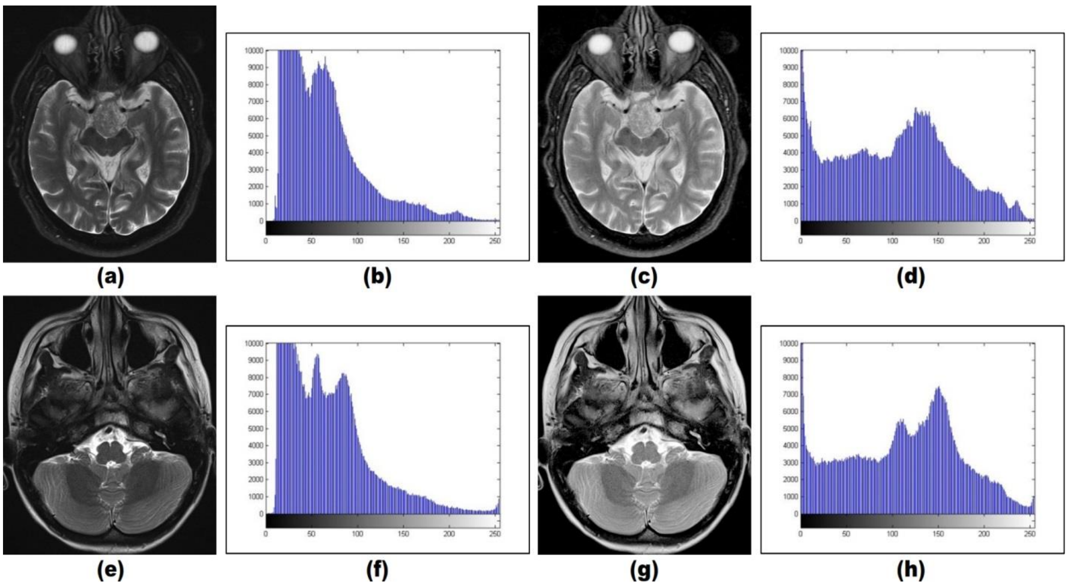

Figure 2. Processing Naturally-Degraded Brain MR Images: (a,e) are Real-Degraded Images; (b,f) are the Histograms of (a,e), Respectively; (c,g) are

the Results of the Tuned Single-Scale Retinex; (d,h) are the Histograms of (c,g), Respectively

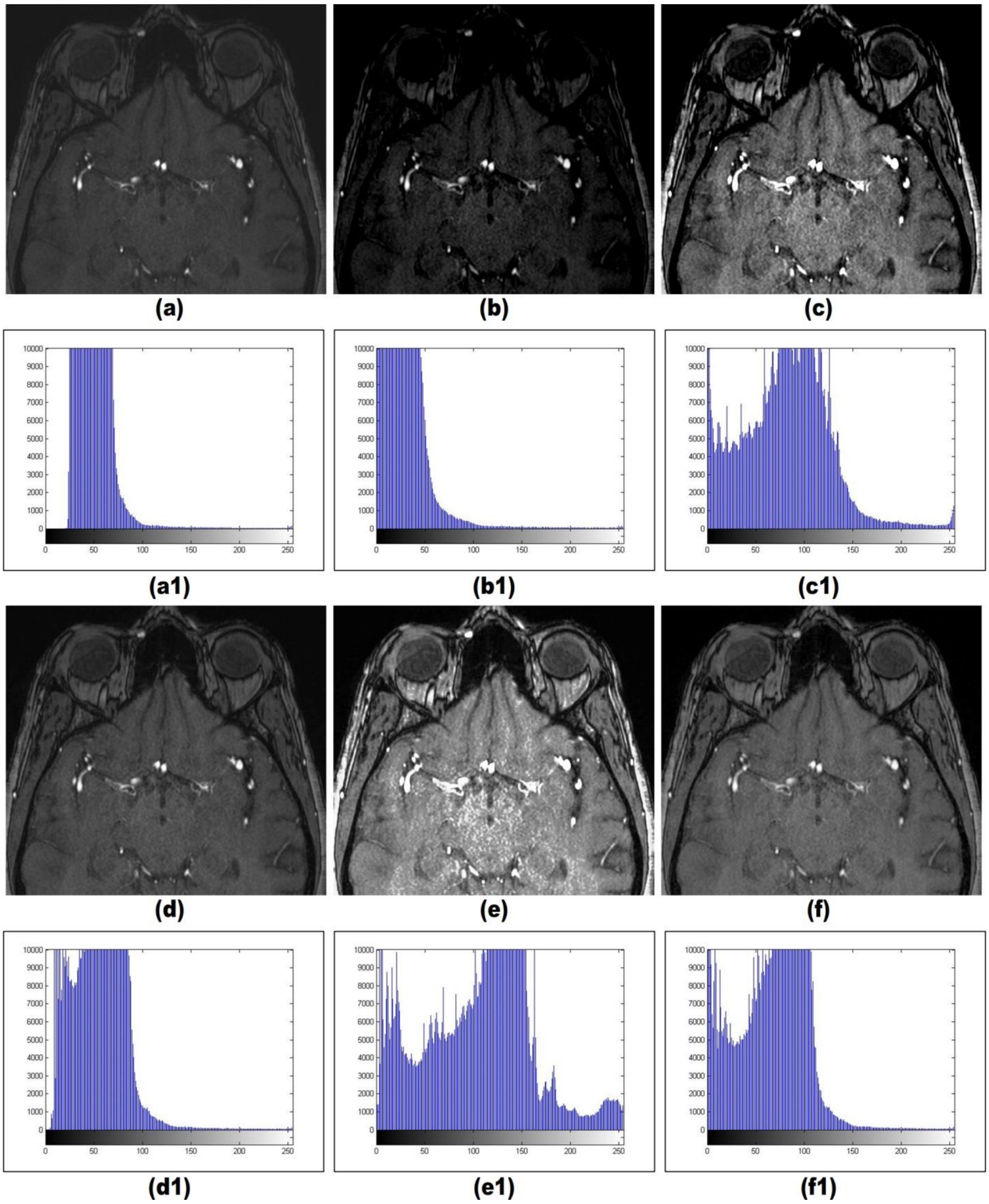

Figure 3. Comparing the Adopted Algorithm with Various State of the Art Algorithms. (a) Naturally-Degraded Brain MR Image; the Rest of the Images are Processed by: (b) Single-Scale Retinex; (c) Gradient Distribution Specification; (d) Type II Fuzzy Set; (e) Recursive Exposure Sub Image Histogram Equalization; (f) Tuned Single-Scale Retinex. Plots from (a1 - f1) are the Histograms of Images from (a - f), Respectively

Furthermore, many comparisons with various methods that utilize contemporary, complex and renowned concepts were achieved to evaluate the performance of the adopted algorithm in terms of visible quality. The comparable methods are namely, single-scale retinex (SSR) [18], gradient distribution specification (GDS) [19], type II fuzzy set (FuzzyII) [12], and recursive exposure sub image histogram equalization (RESIHE) [20]. It is important to mention that all practical experiments were achieved using MATLAB software with a 2.3 core I5 processor and an 8GB of memory.

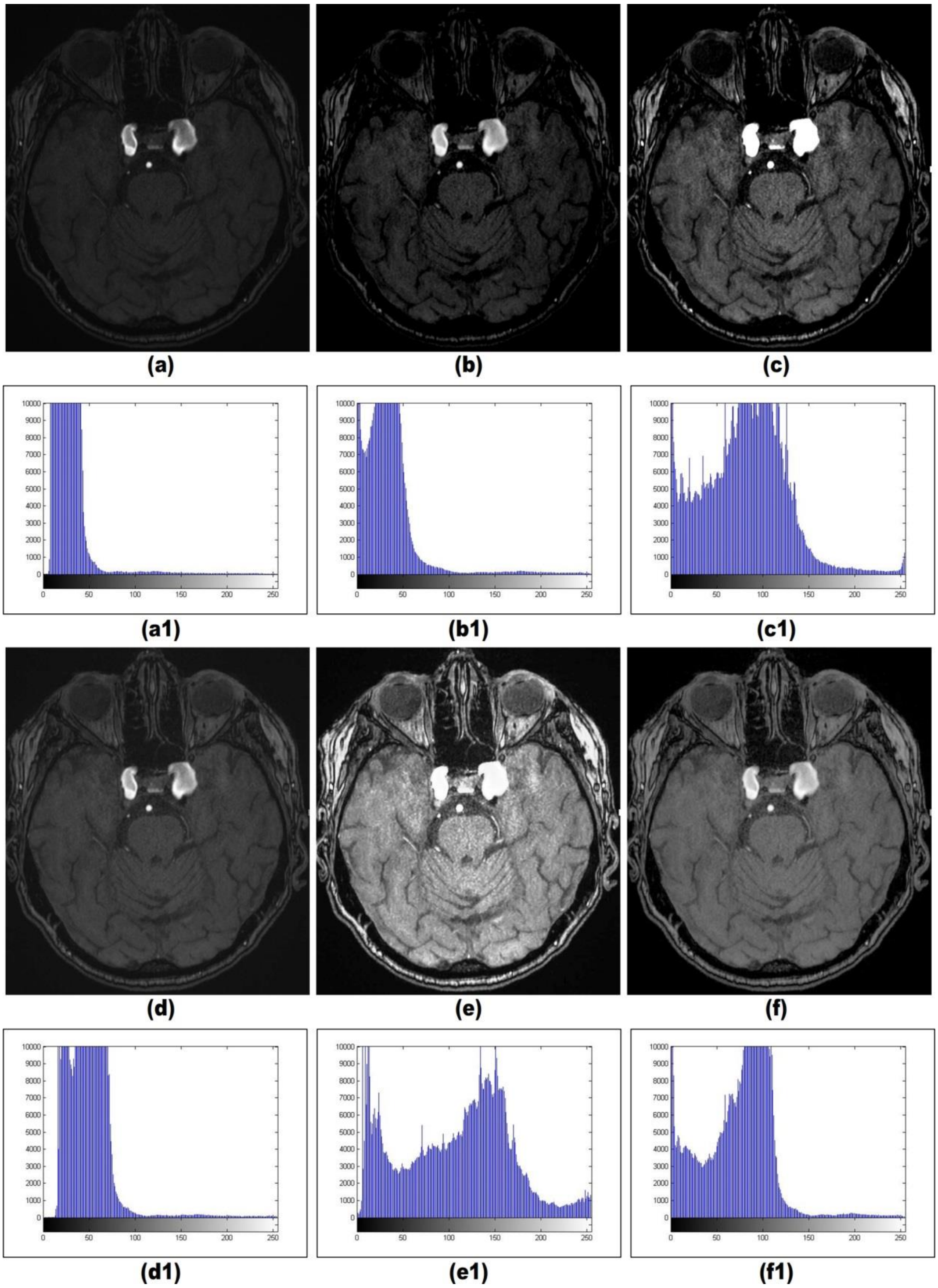

Figure 4. Comparing the Adopted Algorithm with Various State of the Art Algorithms. (a) Naturally-Degraded Brain MR Image; the Rest of the Images are Processed by: (b) Single-Scale Retinex; (c) Gradient Distribution Specification; (d) Type II Fuzzy Set; (e) Recursive Exposure Sub Image

Histogram Equalization; (f) Tuned Single-Scale Retinex. Plots from (a1 - f1) are the Histograms of Images from (a - f), Respectively

To assess the visible quality of the obtained results, the human vision is typically used, since it has been considered as the best mean for measuring the extent of image quality enhancement. In addition, only naturally-degraded MR images are used, in which the reference clear counterparts of such images are unavailable. In many situations, it is difficult to have a reference image, which makes the process of quality assessment not straightforward to perform. Nevertheless, it is preferred to employ an additional unbiased assessment method along with human vision. Therefore, the authors studied many blind assessment methods that can be used when reference images are unavailable. Unfortunately, none of the studied methods provided meaningful results regarding MR images, since there is a lack of methods that can provide efficient assessment for such subject matter. Therefore, the authors decided to provide a histogram for each of the processed images to show what happened to the distribution of pixels after applying both the adopted and the comparable algorithms. The adopted algorithm was appraised with various images obtained from the publicly available databases, for which certain results are exhibited in Figure 1 and Figure 2. Even further, the results of comparisons are shown in Figure 3 and Figure 4. The empirical results in Figure 1 and Figure 2 showed a well perception gain in terms of brightness and contrast, as these aspects improved considerably compared to those in the original images. As well, the deficient dynamic range that characterizes MR images has mended as witnessed by the provided histograms. The proper distribution of pixels in the dynamic range can improve the visible quality of the processed images, and that is the ultimate goal of this study.

The results of comparisons in Figure 3 and Figure 4 revealed that the adopted algorithm is superior to the comparative algorithms in terms of brightness and contrast, in that the obtained results compared favorably to results obtained with more complex algorithms. In the RESIHE-processed images, the bright areas are excessively increased, the image highlight regions are overexposed, the difference in image contrast is large, and the distribution of pixels is irregular. In the FuzzyII-processed images, the exposure of the highlight regions is satisfactory, the variance in image contrast is ordinary, yet the brightness of the results is relatively poor. In the GDS-processed images, the dark areas are overly intensified, the bright areas are overexposed. As well, the image highlight regions are miss exposed, the variance in image contrast is abundant, and the distribution of pixels is unusual. In the SSR-processed images, the dark areas are overly intensified, the image highlight regions are underexposed, the variance in image contrast is high, and the distribution of pixels is unnatural. Providing an expeditious algorithm that effectively processes the deficient dynamic range of MR images is critical. However, such a duty is clearly achieved in which the perceived brightness and contrast are improved, and the viewability of results is better than the original counterparts.

4. Conclusion

In this article, an abridged algorithm for processing the deficient dynamic range of MR images is introduced, in which it is scrutinized with naturally-degraded data collected from publicly available databases. The experimental results showed that the adopted algorithm can improve the brightness and adjust the contrast of degraded MR images, simultaneously. Hence, the processed images have an ameliorated brightness, acceptable contrast, and no visible flaws. The results of comparisons revealed the competence of the adopted algorithm, in that it outperformed the comparable algorithms in terms of brightness and contrast adequacy, which can be seen in the resulted images and their associated histograms. Finally, it is believed that the TSSR algorithm can be further improved to process degraded images from other medical modalities.

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