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MR IMAGES ENHANCEMENT USING RETINEX

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ABSTRACT- Magnetic resonance imaging, or MRI, is a way of obtaining very detailed images of organs and tissues throughout the body without the need for x-rays or "ionizing" radiation. Instead, MRI uses a powerful magnetic field, radio waves, rapidly changing magnetic fields, and a computer to create images that show whether or not there is an injury, disease process, or abnormal condition present. A new method for enhancing the contrast of magnetic resonance images (MRI) by retinex algorithm is proposed. The concept of the retinex, formed from "retina" and "cortex", suggesting that both the eye and the brain are involved, to explain the colour constancy processing of human visual systems. Retinex algorithm can correct the blurring in deep anatomical structures and inhomogeneity of MRI. Multiscale retinex (MSR) employed SSR with different weightings to correct inhomogeneities and enhance the contrast of MR images. The method was assessed by applying it to images acquired on MRI scanner systems. 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). The retinex algorithm successfully corrected a nonuniform grayscale, enhanced contrast, corrected inhomogeneity, and clarified the deep brain structures of MR images captured by surface coils and outperformed histogram equalization, local histogram equalization, and a wavelet based algorithm, and hence may be a valuable method in MR image processing.

KEY WORDS – Magnetic resonance imaging, multiscale retinex, single scale retinex peak signal to noise ratio, contrast to noise ratio.

1. INTRODUCTION - Magnetic resonance imaging is a medical imaging technique used in radiology to visualize internal structures of the body in detail. Over the past twenty years, magnetic resonance imaging (MRI) has become one of the most important imaging modalities available to clinical medicine. It offers great technical flexibility, and is free of the hazards associated with ionizing radiation.MRI makes use of the property of nuclear magnetic resonance (NMR) to image nuclei of atoms inside the body[1]. Several techniques have been recently developed to improve the detection and diagnosis capabilities including eliminating artifacts and enhancing the contrast of MR images presence [2]. Zoroofi et al. [4] proposed a post processing technique to reduce MRI body motion artifacts due to the presence of an object on the imaging plane. They proposed a reconstruction algorithm, based on a superposition bilinear interpolation algorithm, reducing such artifacts with a minimum-energy method to estimate the unknown parameters of body motion Results showed feasibility in clinical application. Sled et al. [5] demonstrated the efficacy of an automatic nonparametric method in correcting intensity nonuniformities using both real and simulated MR data. Ahn et al. [6] used Method of local adaptive template filtering for enhancing the signal-to-noise ratio (SNR) in MRI without reducing the resolution. Moreover, Styner et al. [7] showed parametric bias-field correction method could correct bias distortions that are much larger than the image contrast. Likar et al. [8] used a model-based correction method to adjust inhomogeneity in the intensity of an MR image. They applied an inverse image-degradation model where parameters were optimized by minimizing the information content of simulated and real MR data.

Lin et al. [9] used a wavelet based algorithm to approximate surface-coil sensitivity profiles. They corrected image intensity in homogeneities acquired by surface coils, and used a parallel MRI method to verify the spatial sensitivity profile of surface coils from the images captured without using a body coil. It has also been shown that contrast enhancement can be used to improve the quality of MR images [10, 11].

Several MRI-related techniques have been suggested to facilitate more accurate clinical diagnoses. Among them, surface coils were used to enhance the SNR and improve the resolution [12]. A surface coil consisted of conductive loops that transmit radiofrequency

(RF) energy can also be used as receivers. They exhibited maximal sensitivity in localizing surface structures and facilitate faster MRI scanning [12-15]. The use of stronger gradients increased the spatial resolution but reduced the sensitivity. Nevertheless, the location of surface coils must be controlled to increase sensitivity. Image quality can be improved by reducing the thermal noise generated outside the region of sensitivity, eliminating artifacts due to body movements and respiration, and using steep imaging gradients. Another obvious disadvantage of planar surface coils was that the low signal level made it difficult to image deep brain structures, resulting in a large dynamic range of signal intensities in MR images. Dynamic-range compression has been used to solve this problem [11, 12] with views of larger regions being captured by a phased array of surface coils [13]. Phased-array surface coils can be implemented by switching among multiple surface-coil receivers. This improved the SNR and increased the clinical applications, but the problem of signal loss in deep brain structures remained. Therefore, an optimum contrast enhancement algorithm would be helpful to improve the quality of MR images acquired by surface coils. Stretching the pixel dynamic range of certain objects in an image is a widely adopted approach for enhancing the contrast [15, 16].

The image contrast-enhancement techniques can be divided into two types: global and local histogram enhancement. The (global) histogram equalization technique improved the uniformity of the intensity distribution of an image 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 [17-19]. Local histogram enhancement 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 neighbouring 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. For image processing, the presence of the nonuniformity of an MR image caused by the inhomogeneity of the magnetic intensity is very similar to that of a normal image resulted from bad illumination sources and environmental conditions [20-23].

To address the nonuniformity problem of an image, Land et al [24], inspired by the psychological knowledge about the brains processing of image information from retinas, developed a concept named retinex as a model for describing the colour constancy in human visual perception. His idea is that the perception of human is not completely defined by the spectral character of the light reaching the eye from scenes. It includes the processing of spatial-dependant colour and intensity information of the retina of an eye, which can be realized by the computation of dynamic-range compression and colour rendition. Although hardware techniques can be utilized to correct the image inhomogeneity and to enhance image contrast, they are costly and inflexible. Hence, it is promising to develop easy and low-cost software-based techniques to address the inhomogeneity problem in MR images [25]. In this paper, we introduced a software-based retinex algorithm for contrast enhancement and dynamic-range compression that improve image quality by decreasing image inhomogeneity.

2. METHODE

2.1 RETINEX ALGORITHM

Digital cameras become extraordinarily convenient in daily life, although images obtained with such cameras suffer from a loss in clarity of details and colour as the light levels drop within shadows, or as distance from a lighting source increases. This is due to the fact that cameras only capture the light reflected by the scene, while human beings could adjust automatically to the variation of light. This problem is known as colour constancy. Colour constancy refers to the steady psychological perception for the colour of a scene when light varies. People maintain approximate colour constancy despite variation in the colour of nearby objects and despite variation in the spectral power distribution of the ambient light. Land's Retinex (retinal-cortical) theory is the first computational model to explain and achieve colour constancy. It is based on a series of psychophysical experiments. The purpose of the Retinex is to compute lightness values that will be invariant under changes of viewing context, as human performance is roughly invariant under similar changes have become extraordinarily convenient in daily life, although images obtained with such cameras suffer from a loss in clarity of details and colour as the light levels drop within shadows, or as distance from a lighting source increases. This is due to the fact that cameras only capture the light reflected by the scene, while human beings could adjust automatically to the variation of light. This problem is known as colour constancy.

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2.1.1 SINGLE SCALE RETINEX

The Retinex is a human perception based image processing algorithm which provides "COLOUR CONSTANCY or COLOUR/LIGHTNESS RENDITION" and "DYNAMIC RANGE COMPRESSION".

Single Scale Retinex can either achieve "COLOUR / LIGHTNESS RENDITION" or "DYNAMIC RANGE COMPRESSION", but not both simultaneously.

A common problem with colour imagery digital or analog is that of successful capture of the dynamic range and colour seen through the viewfinder onto the acquired image. This image is poor rendition of the actual observed scene.

A distinct trade of f controlled by the scale of surrounded function exist between the dynamic range compression and tonal rendition and one can improve only at the cost of reducing the other. The magnitude of the scale determines the type of information that the retinex provides:

1. Smaller scale providing more dynamic range compression.
2. Larger scale providing more colour constancy.

Jobson and his co-worker defined a single-scale Retinex (SSR), which is an implementation of centre/surround Retinex.The Single-scale retinex is given by

$$R_i(x,y) = \log I_i(x,y) - \log[F(x,y) * I_i(x,y)] \quad (1)$$

Where Ii(x, y) is image distribution in the ith colour band, F(x, y) is the normalized guass function, C is the Gaussian surround space constant and $R_{i(}$x, y) is the retinex output

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

Gaussian function: F(x, y) =$Ke^{-(x2+y2)/c2}$

The image distribution is the product of scenes reflectance and illumination.

$$I_i(x,y) = S_i(x,y) r_i(x,y) \quad (3)$$

Where Si(x, y) is the spatial distribution of illumination and ri(x, y), the distribution of scene reflectance. The convolution with surround function works as averaging in the neighbourhood.

Generally the illumination has slow spatial variation, which mean

$$R_i(x,y) = \log \frac{S_i(x,y) r_i(x,y)}{\overline{S_i(x,y)}\,\overline{r_i(x,y)}} \quad (4)$$

.

$$S_i(x,y) \approx \overline{S_i(x,y)}$$

(5)

$$R_i(x, y) \approx \log \frac{r_i(x, y)}{r_i(x, y)} \tag{6}$$

Hence the illuminance term can be eliminated from the retinex obtained making colour constancy possible.

Jobson et al [25] stated that Gaussian had the property of being more "regional" and offered good dynamic range compression over a large range of space constant. The selection of space constant is related with visual angel in the direct observation. But the value cannot be theoretically modelled and determined. Depending on the special scale, it can either provide dynamic range compression (small scale) or tonal rendition (large scale).

Steps involved in implementation of SSR-

- Read image and convert size front unit 8 to double.
- Define RGB components and convert size to double. Obtain log transform to compress dynamic range. Obtain FFT
- Assume scale values as 15, 80 and 250.
- Create 2D mesh grid for the image.
- Define gauss pdf function, normalize its value and obtain FFT.
- Multiply the FFTs and obtain the SSR for each colour component.
- Concatenate the new components obtained and obtain the final SSR image.

2.1.2 MULTI SCALE RETINEX-

The MSR combines the dynamic range compression of the small scale retinex with the tonal rendition of the large scale retinex to produce an output which a compasses both.

The advantages that the MSR has over the SSR are in the combination of scales which provide both dynamic range compression and tonal rendition at the same time. The overall result of the application of MSR is still more saturated than human observation giving the final image a washed out appearance but, it preserves most of the detail in the scene. This greying of areas of constant intensity occurs because the retinex processing enhances each colour band as a function of its surround. The smaller value in the weaker channel gets pushed up strongly, making them approximately equal to in magnitude to the dominant channel, leading to a greying out of the overall region.MSR produces a much better final images in terms of colour constancy and dynamic range compression than SSR.

Because of the trade-off between dynamic range compression and colour rendition, we have to choose a good scale c in the formula of F(x, y) in SSR. If we do not want to sacrifice either dynamic range compression or colour rendition, multiscale retinex, which is a combination of weighted different scale of SSR, is a good solution,

$$R_{MSRi} = \sum_{n=1}^{N} \omega_n R_{ni} \tag{6}$$

$$R_{MSRi} = \sum_{n=1}^{N} \omega_n \{\log I_i(x, y) - \log[F_n(x, y) * I_i(x, y)]\} \tag{7}$$

Where N is the number of the scales, Rni is the ith component of the nth scale. The obvious question about MSR is the number of scales needed, scale values, and weight values. 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. But these are more experimental than theoretical, because we do not know the scale of image to the real scenes. The weights can be adjusted to weight more on dynamic range compression or colour rendition.

Steps involved in implementation of MSR-

- Read image and convert size from unit 8 to double.
- Define RGB components and convert size to double. Obtain log transform to compress dynamic range. Obtain FFT
- Assume scale values as 15, 80 and 250.
- Create 2D mesh grid for the image.
- Define gauss' pdf function, normalize its value and obtain FFT for each sigma value.
- Multiply the FFTs for one colour component with the gauss pdfs for each sigma value
- Introduce weights for each sigma component in the obtained result and obtain the SSR for each colour component.

Concatenate the new components obtained and obtain the final MSR image.

2.1.3 PSNR (PEAK SIGNAL TO NOISE RATIO)-

The peak signal-to-noise ratio (PSNR) is defined as

$$\text{PSNR} = 20\log\frac{ipeak}{\sqrt{\sum\frac{\{y(k,l)-m(k,l)\}}{k,l}}} \quad (8)$$

Where $y(k, l)$ and $m(k, l)$ were the enhanced and original images of size K and L respectively,
And ipeak was the maximum magnitude of images.

3. COMPARISION TO OTHER TECHNIQUES

3.1 Non-linear gamma correction

Good visual representations seem to be based upon some combination of high regional visual lightness and contrast. To compute the regional parameters, we divide the image into nonoverlapping blocks that are 50×50 pixels. For each block, a mean, I, and a standard deviation, σ_f, are computed. A first approach was to postulate that for visually good rendition the contrast × lightness product should be above a minimum value, with the additional constraint that each component cannot fall below an absolute minimum value.

This regional scale is sufficiently granular to capture the visual sense of regional contrast. Both the contrast and the lightness can be measured in terms of the regional parameters. The overall lightness is measured by the image mean, which is also the ensemble measure for regional lightness. The overall contrast, σ_f, is measured by taking the mean of σ_f, and it provides a gross measure of the regional contrast variations. The global standard deviation of the image did not relate, except very weakly, to the overall visual sense of contrast. Image frame sizes ranged from 512×512 to 1024×1024 pixels.

The coupling of the constraints of minimum contrast-lightness product with minimum contrast and lightness as separate entities defines the zone in figure labelled “visual good”. Further, this figure suggests that there may exist a contour of much higher contrast-lightness, which can be considered a “visual ideal”.

When images are displayed on monitors, their intensity profile is typically modified using the gamma-Transformation given by:

$I_o(x, y) = [I_i(x, y)]$ ^1/γ (9)

,

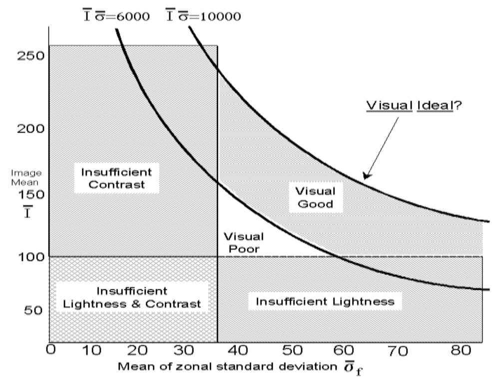


Figure 1 shows Variation of image intensity and contrast

Where, *Ii(x, y)* is the input value, and $I_o(x, y)$ is the modified value.
A value of is γ-1 the linear transform. In order to gauge our results against a linear baseline for the original image data, we determined that most digital images are super-linear and should be corrected to approximate linearity by gamma transforming the processed image using γ =0.63

While this has negligible effect on standard deviation values, it just adjusts the mean downward from about 165 to about 128.

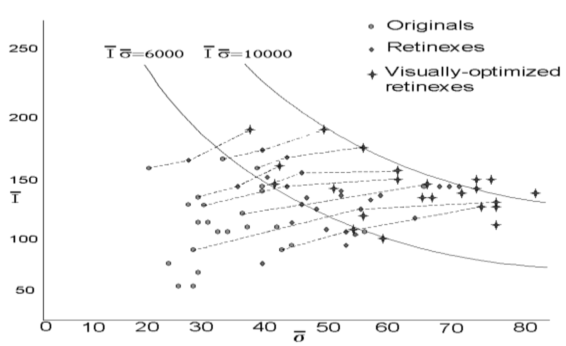


Figure 2 Showing visually optimal area

3.2 Histogram Equalization

A global technique that works well for a wide variety of images is histogram equalization. This technique is based on the idea of remapping the histogram of the scene to a histogram that has a near-uniform probability density function. This results in reassigning dark regions to brighter values and bright regions to darker values. Histogram equalization works well for scenes that have unmolded or weakly bi-modal histograms (i.e. very dark, or very bright), but not so well for those images with strongly bi-modal histograms (i.e. scenes that contain very dark and very bright regions).

3.3Homomorphic Filtering

The technique is that most resembles conceptually and functionally is homomorphic filtering. The image is first passed through a logarithmic non-linearity that provides dynamic range compression. It is then Fourier transformed, and its representation in the spatial frequency domain is modified by applying a filter that provides contrast enhancement. The modified image is then inverse Fourier transformed and is passes through an exponential non-linearity that 'reverses' the effects of the logarithmic nonlinearity.

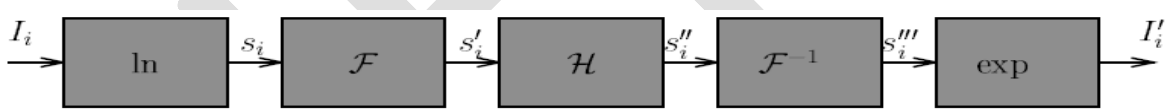
Homomorphic filter is used for image enhancement. It simultaneously normalizes the brightness across an image and increases contrast. Here homomorphic filtering is used to remove multiplicative noise. Illumination and reflectance are not separable, but their approximate locations in the frequency domain may be located. Since illumination and reflectance combine multiplicatively, the components are made additive by taking the logarithm of the image intensity, so that these multiplicative components of the image can be separated linearly in the frequency domain. Illumination variations can be thought of as a multiplicative noise, and can be reduced by filtering in the log domain.

To make the illumination of an image more even, the high-frequency components are increased and low-frequency components are decreased, because the high-frequency components are assumed to represent mostly the reflectance in the scene (the amount of light reflected off the object in the scene), whereas the low-frequency components are assumed to represent mostly the illumination in the scene. That is, high-pass filtering is used to suppress low frequencies and amplify high frequencies, in the log-intensity domain.

Mathematically,

$$s_i(x, y) = \ln[I_i(x, y)] \quad (10)$$
$$s_i^{1}(v, w) = F[s_i(x, y)] \quad (11)$$
$$s_i^{11}(v, w) = s_i^{1}(v, w)H(v,w) \quad (12)$$
$$s_i^{111}(x, y) = F^{-1}[s^{11}(v, w)] \quad (13)$$
$$I_i^{1}(x, y) = \exp[s_i^{111}(x, y)] \quad (14)$$

H represents the homomorphic filter. It is in its final exponential transform that the homomorphic filter differs the most from the MSR. MSR does not apply a final inverse transform to go back to the original domain.



Homomorphic filtering[9]

Figure 3 shows Block diagram for Homomorphic filtering

The homomorphic filter consistently provided excellent dynamic range compression but is lacking in final colour rendition. The output of the homomorphic filter in effect appears extremely hazy compared with the output of the MSR though the dynamic range compression of the two methods appears to be comparable.

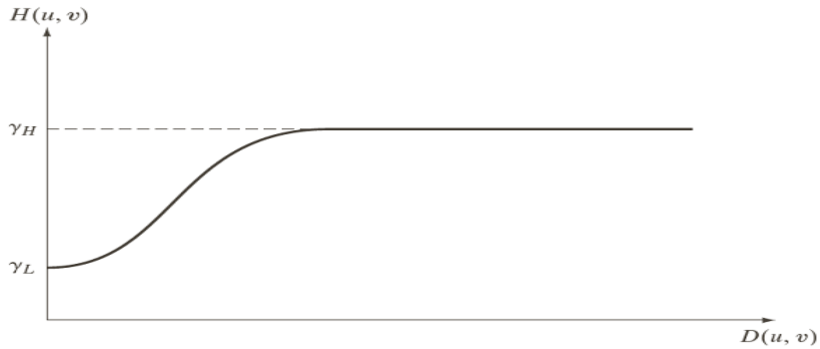


Figure 4 shows Characteristics of homomorphic filter used

3.4 Manual Image Enhancement

As both professional and amateur photographers face the limitations of the narrow dynamic range in current printing technology, and the inadequate performance of image enhancement algorithms, more and more attention is being focused on manual enhancement methods. One such technique is ‘burning-and-dodging’ where different regions of an image are interactively modified by a user'. The burn and dodge tool provides the capability of modifying the colour content of a region by using tools of varying sizes and shapes that work as electronic “scrims.”

We have provided a brief description of the commonly encountered “problems” introduced inevitably in a digital image due to the nature of the acquisition process and the pre-processing algorithms. Since in many image enhancement applications—e.g. images obtained from the Internet— we neither know the source of the image (digital camera or scanner), nor do we know how the images have been “enhanced,” it is critical that we understand the effects of these common processes on the output of the MSR.

We recognize that in such cases, slight modifications to the canonical set of constants may need to be made in order to obtain the best possible visual quality. However, though the presence of these operations in the input image can adversely affect the overall visual quality of the output image produced by the MSR, even the ‘not-the-best’ MSR output is still typically better than the original image in terms of contrast, visual quality.

The MSR has thus proven to be quite resilient to many of the arbitrary operations that are used in digital image formation and can thus be truly considered a fully automatic process.

4. Result and Discussion

Selected results for diverse test cases

- The test images presented here begin with some test scenes. We feel it is fundamental to refer the processed images back to the direct observation of scenes. This is necessary to establish that how well the computation represents a result that is; “what you would have seen if you would have been there”.

- Clearly we cannot duplicate human vision visions, peripheral vision which spans almost 180^{o} but within the narrower angle of most image frames we would like to demonstrate that the computation achieves the clarity of colour and detail in shadows, reasonable colour constancy and lightness and colour rendition that is present in direct observation of scenes. While we cannot yet test performance for scenes that go beyond 8 bit dynamic ranges, these results support the utility for the processing scheme for the enhancement of conventional 8-bit colour images.

The test scenes are given first so that we can describe the degree to which the computation approaches human visual performance. All the test scene images after retinex processing are quite "true to life" compared with direct observation. We did not carefully match camera spatial resolution to observation so some difference in perceived detail is expected and observed. However overall colour lightness and detailed rendering for the multi scale retinex is a good approximation to human visual perception.

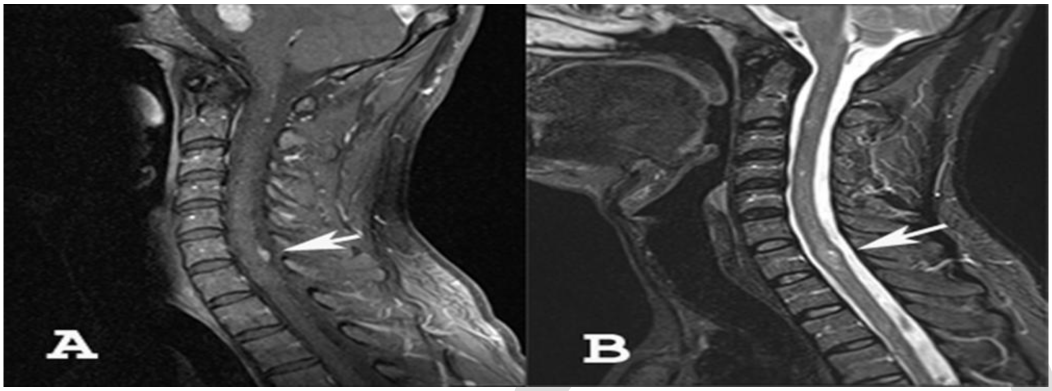


Figure 5 shows the MR image of cervical spine fig A original image fig B retinex output.

3. CONCLUSION

The inhomogeneity and anatomic-structure blurring found in images captured by surface receiving coils was due to variations in image brightness. The inhomogeneities of MR images were very low frequency components in frequency domain of images. The retinex algorithm especially performed to remove the very low frequency components of images by an estimator constructed with a similar low pass filter from a Gaussian surround function as described in for the purpose of correction of the inhomogeneous MR images. The variations of inhomogeneity in MR images received. Hence, MR post processing techniques were crucial in improving the structural details and homogeneity of such brain images. In the present study, we proposed an easy, low-cost software-based method to solve these problems, also avoiding expensive charges to the imaging hardware. Our novel retinex algorithm successfully corrected a nonuniform greyscales, enhanced contrast, and corrected inhomogeneity.

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