# Analysis of Background Detection and Contrast Enhancement of MRI Images

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## ABSTRACT

This paper presents a new method for poor lighting contrast enhancement of MRI images based on the Weber's law. Background of MRI images is identified by using the contrast enhancement transformations. The contrast image transformation can be defined by two operators: opening and closing. The first operator employs information from block analysis, while the second transformation utilizes the opening by reconstruction. Opening by reconstruction is used to define the multi background notion. The objective of contrast operators is normalizing the grey level of an input MRI image by using the contrast operator. The normalization process will enhance the quality of MRI images by avoiding abrupt changes in intensity among different regions.

## Keywords

Image background, morphological contrast, morphological filters by reconstruction, multi background, Weber's law.

## 1. INTRODUCTION

Magnetic Resonance imaging is an imaging technique used primarily to produce the medical images of the human body for prognosis. It is very necessary to enhance the contrast of such images before further processing or analysis can be conducted [13]. Image enhancement is a challenging research area in image processing. Its principal objective is to process an image so that the result is more suitable than the original image for a specific application. There are several techniques to enhance an image.

Image enhancement is a technique that increases the visual contrast of an image in a designated intensity range or ranges. Brain Images are often characterized not by particular objects, but by the global configuration of cerebrospinal fluid (CSF), gray matter (GM), white matter (WM) and white matter lesion (WML). The visual appearance of these images may be considerably improved by highlighting its high frequency contents to enhance the edge and detail information in it [14].

The background in poor lighting of grey level MRI images can be identified by the use of morphological operators. Lately, image enhancement has been carried out by the application based on Weber's law. After that erosion and dilation and opening by reconstruction method is followed.

This paper is organized as follows. Section 2 describes the contrast enhancement. Section 3 presents a brief description about Weber's 'law and some morphological transformations. Section 4 gives an approximation to the background by means of block analysis in conjunction with transformations that enhance MRI images with poor lighting. In Section 5, the multi background notion is introduced by means of the opening by reconstruction. Section 6 describes histogram equalization algorithm and Section 7 describes PDE enhancement. Section 8 shows an experimental result analysis and discussion. Finally, conclusions are presented in Section 9.

## 2. CONTRAST ENHANCEMENT

The image enhancement includes the improvement of the visibility and perceptibility of the various regions. Which an image can be partitioned and defect ability of the image features inside the regions. Image enhancement is usually followed by detection of features such as edges, peaks, and other geometric features which is of paramount importance in low-level vision. We can see that the enhanced image is a shaper image than the original. Particularly interesting is the fact that textural information has been rendered visible in the enhanced image.

## 3. MORPHOLOGICAL TRANSFORMATIONS AND WEBER'S LAW

***a)*** *Definitions of morphological transformations:*

In mathematical morphology, increasing and idempotent transformations are frequently used morphological transformations complying with these properties are known as morphological filters [7]-[9].The basic filters are morphological opening and morphological closing using a structural element. The morphological opening and closing can be expressed as follows.

$$\gamma_{\mu\mathrm{B}}(f)(x) = \delta_{\mu\mathrm{B}}(\varepsilon_{\mu}\mathrm{B}(f))(x)$$
$$\varphi_{\mu\mathrm{B}}(f)(x) = \varepsilon_{\mu\mathrm{B}}(\delta_{\mu}\mathrm{B}(f))(x)$$

Where the morphological erosion $\varepsilon_{\mu}\mathrm{B}(f)(x)$ and morphological dilation $\delta_{\mu}\mathrm{B}(f)(x)$ are

$$\varepsilon_{\mu}\mathrm{B}(f)(x) = \wedge\{f(y): y \in \mu\mathrm{B}_x\}$$ and

$$\delta_{\mu}\mathrm{B}(f)(x) = \vee\{f(y): y \in \mu\mathrm{B}_x\}$$, respectively.

Here, $\wedge$ is the inf operator and $\vee$ is the sup operator.

b) *Weber's law:*

Weber's law states that, it is the ratio of the difference in max to min luminance value to the min luminance value and it is denoted by C [12].

$$C = \frac{L_{\max} - L_{\min}}{L_{\min}}$$

If L= $L_{\min}$ and ΔL= $L_{\max} - L_{\min}$, can be rewritten as

$$C = \frac{\Delta L}{L}$$

This indicates Δ (log L) is proportional to C; therefore, Weber's law can be expressed as [5]

$$C = k \log L + b \quad L>0$$

Where, k and b are constants, b being the background.

## 4. IMAGE BACKGROUND APPROXIMATION BY BLOCKS

When D represents the digital space under study, with D= $Z^2$ and Z the integer set. In this way, let D be the domain of definition of the function f. The image f is divided into n blocks $w^i$ of size $l_1 \times l_2$ . Each block is a sub image of the original image. The minimum and maximum intensity values in each sub image are denoted as $m_{i,} M_i$ .

For each analyzed block the background criteria is found by the following way.

$$\tau_i = \frac{m_i + M_i}{2} \qquad \forall_i = 1, 2, \ldots.n$$

Where $\tau_i$ represents a division line between clear (f> $\tau_i$ ) and dark (f $\leq$ $\tau_i$ ) intensity levels.

The grey level images are used in this is a constant $k_i$ is obtained as follows:

$$k_i = \frac{255 - m_i^*}{\log(256)} \qquad \forall_i = 1, 2, \ldots.n$$

## 5. IMAGE BACKGROUND DETERMINATION USING THE OPENING BY RECONSTRUCTION

Instead of dividing the original images into no of blocks and without using the Erosion and Dilation property a new method is used here. In this method the morphological transformations generate a new contour when the structuring element is increased. While using morphological erosion or dilation which touches the regional minimum and merges it with the regional maxima to detect the background criteria [11]. In this method the background detection method is same as the above method but the only thing is the way to detect the background is modified and the background criteria detection is given by the following expression

$$\tau(x) = \overleftarrow{\nu}_{\mu}(f)(x).$$

By having the value of the structuring element size to be a constant one it is observed that we can able to get a clear image.

## 6. HISTOGRAM EQUALIZATION

Histogram equalization is one of the well known image enhancement technique. It became a popular technique for contrast enhancement because this method is simple and effective. In the latter case, preserving the input brightness of the image is required to avoid the generation of non-existing artifacts in the output image. Although these methods preserve the input brightness on the output image with a significant contrast enhancement, they may produce images with do not look as natural as the input ones. The basic idea of histogram equalization method is to re-map the gray levels of an image. HE tends to introduce some annoying artifacts and unnatural enhancement.

This technique is widely used to improve images with poor lighting. The histogram equalization technique consists in reordering the grey level intensities within the image to obtain a uniformly distributed histogram.

## 7. PARTIAL DIFFERENTIAL EQUATION

A traditional method of image enhancement is hard to read the goal out exactly from the low contrast image, and it needs for much iteration, both time-consuming and less obvious. Based on nonlinear partial differential equations, this paper raised an algorithm to enhance the weak goal. It can effectively improve the readability of the image. Besides, for its reducing the number of iterations, it had a great improvement in efficiency. This method can be applied to real-time processing of video images in the dark. [16].

**Algorithm:**

The core code of this algorithm as follows

$$t1 = \exp((-row^2 - col^2)/4/e);$$

$$t2 = \exp((-I.^2 * c^2 / 4 / (e^{-3}) * t1^2 * (row + col)^2) / k^2);$$
$$t3 = I.*8 - N - S - W - E - EN - ES - WS - WN;$$
$$t4 = (1+w)*t2 - w;$$

```
        if (I<=e)
          h=0;
      else if (I>=A*e)
              h=1;
      end
          end
```

$$I = I + (I.*(1-h) + h*I.*t3).*t4;$$

Where I is one image to be processed, w=w, k=k, e=e0. t1 t4 are the middle of the volumes. According to t1, t2, we get g (I), while from t3, we get div ( $(\nabla I \div |\nabla I|)$ and [(1+*W*) *G* (| $\nabla$ *G* $\ast$ $\nabla$ *u*|) − *w*] is from t4. In accordance with the number of iteration, the above codes carry out in cycle.

## 8. EXPERIMENTAL RESULT ANALYSIS AND DISCUSSION

The proposed methods for enhancing the poor lighting brain image have been implemented using MATLAB. The results of each method are analyzed by using statistical parameters such as PSNR, CNR, MSE, SSIM and FOM. The detailed descriptions of these Statistical parameters are given bellow.

### *8.1. FOM( Figure Of Merit)*

The figure of merit (FOM) is the edge preserving measure that is defined as below.

$$FOM = \frac{1}{Max\left\{\hat{N}, N_{ideal}\right\}} \sum_{i=1}^{\hat{N}} \frac{1}{1 + d_i^2 \lambda}$$

In this equation $\hat{N}$ and $N_{ideal}$ are the numbers of detected and original edge pixels, respectively; $d_i$ is the Euclidean distance between the *i* th detected edge pixel and the nearest original edge pixel; λ is a constant typically set to 1/9. The dynamic range of *FOM* is between the processed image and the ideal image. We used the canny edge detector to find the edge in all processed results.

### *8.2. PSNR (Peak Signal-to-Noise Ratio)*

The phrase peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. To calculate PSNR value, use the following formula.

$$PSNR = 10 \log \left( \frac{\sigma_s^2}{\sigma_{\hat{s}}} \right)$$

Where,

S – Referenced image

$\hat{S}$ - Filtered image.

$\sigma_s^2$ = variance of the Referenced image

$\sigma_{\hat{s}}^2$ = variance of the Filtered image

### *8.3. MSE (Mean Squared error)*

MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. Mean squared error formula as follows.

$$MSE = \frac{1}{MN} \sum_{(i,j)=1}^{MN} \left( S(i,j) - \hat{S}(i,j) \right)^2$$

Where,

S - Reference image

$\hat{S}$ - Filtered image.

### *8.4. SSIM (Structural Similarity Index)*

The structural similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index is a full reference metric, in other words, the measuring of image quality based on an initial uncompressed or distortion-free image as reference. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proved to be inconsistent with human eye perception.

The SSIM metric is calculated on various windows of an image. The measure between two windows *x* and *y* of common size *N*×*N* is:

MN= size of the reference image and filtered image

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Where,

$\mu_x$ = Average of x;

$\mu_y$ = Average of y;

$\sigma_x^2$ = Variance of x;

$\sigma_y^2$ = Variance of y;

$\sigma_{xy}$ = Covariance of x and y;

$c_1 = (k_1L)^2, c_2 = (k_2L)^2$ - Variables to stabilize the division with weak denominator;

$L$ - Dynamic range of the pixel-values (typically this is $2^{\#bitsperpixel-1}$);

$k_1 = 0.01 \quad k_2 = 0.03$ (Default values).

### 8.5. CNR (CARRIER-TO-NOISE RATIO)

The carrier-to-noise ratio is defined as the ratio of the received modulated input power *C* to the received noise power *N* after the receive filters:

$$CNR = \frac{C}{N}$$

When both carrier and noise are measured across the same impedance, this ratio can equivalently be given as

$$CNR = \left(\frac{V_C}{V_N}\right)^2$$

Where, $V_C$ and $V_N$ are the root mean square (RMS) voltage levels of the input and noise respectively. *C*/*N* ratios are often specified in decibels (dB):

$$CNR_{dB} = 10\log_{10}\left(\frac{C}{N}\right) = C_{dB} - N_{dB}$$

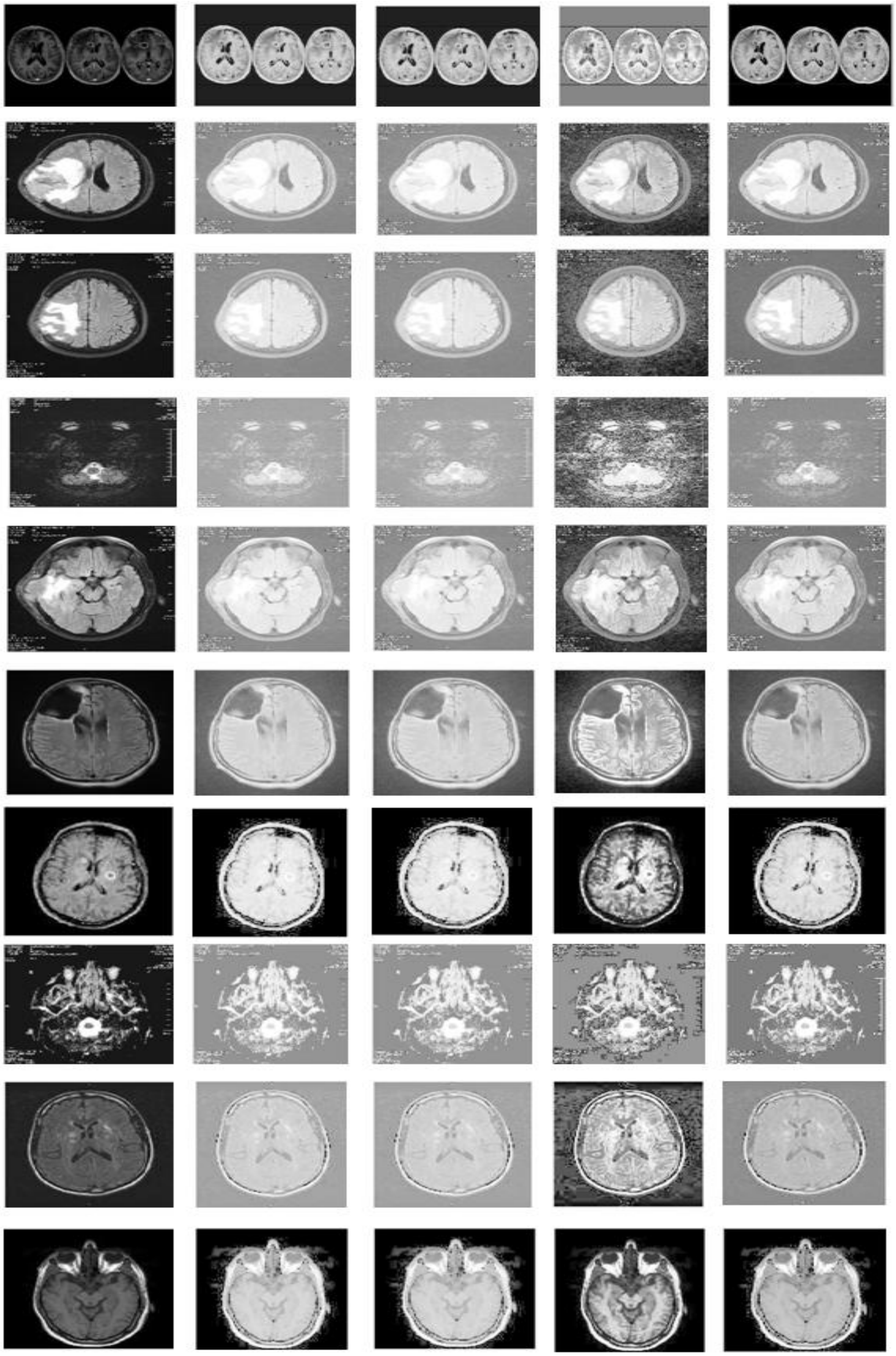
Or in term of voltage:

$$CNR_{dB} = 10\log_{10}\left(\frac{V_C}{V_N}\right)^2 = 20\log_{10}\left(\frac{V_C}{V_N}\right)$$

The *C/N* ratio is measured in a manner similar to the way the signal-to-noise ratio (*S/N*) is measured, and both specifications give an indication of the quality of a communications channel.

**Table 1: Average values of performance analysis**

| Methods | FOM | SSIM | MSE | CNR | PSNR |
|---|---|---|---|---|---|
| **BM** | 4.2415 | 0.1383 | 0.7646 | 17.220 | 50.031 |
| **OM** | 4.6860 | 0.1398 | 0.5754 | 19.457 | 36.627 |
| **HIST** | 3.8878 | 0.1470 | 0.5582 | 16.683 | 21.407 |
| **PDE** | **3.8457** | **0.2571** | **0.0583** | **4.2809** | **17.609** |



(a) (b) (c) (d) (e)

**Figure 1: (a) Original images (b) Block Method (c) Opening Method (d) HE Method (e) PDE Method**

The experiment is conducted over the different MRI images with required statistical parameters and their average result is shown in table 1. The performance analysis chart is presented among various parameters in figure 2. The computational results clearly explain that the PDE method is performing better than other. Since FOM, MSE, and CNR value are low, at the same time SSIM value is high.

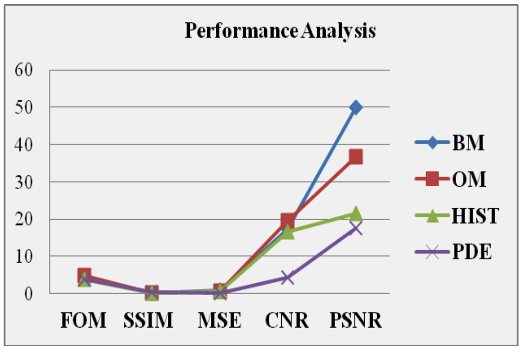



**Figure 2: Performance analysis**

## 9. CONCLUSION

MRI image quality is enhanced with the help of background detection and contrast enhancement transformations. This is very effective in enhancing the MRI images. These contrast transformations are characterized by the normalization of grey level intensities and it is observed that by the use of the opening by reconstruction or by the use of erosion dilation methods. These contrast enhancement transformations are based on Weber's law. After detect the background using opening by reconstruction, PDE gives satisfactorily result in MRI images. As a result MRI images that have been applied with this technique appear to be clearer and hopefully would easy further analysis.

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