

## MRI Brain Image Enhancement Using an Improved Contrast Enhancement Method

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### Abstract

*The uncontrollable cells growth in the brain portion is the main reason for cancer deaths nowadays. So, effective detection of brain tumors is more important in the medical field to analyze the tumor portion. Detecting tumors prior and diagnosis of tumors can play a major role in preventing human death due to brain tumors. To detect the tumor portion, many segmentation and classification methods have been proposed. For the effect segmentation process, enhancing brain images is necessary. In this present paper, Magnetic resonance imaging (MRI) brain images have been taken as test images. The proposed enhancement method has two major phases. The first phase contains a regularization process in two steps to equalize the test images' intensities, and the second phase contains a mapping process of two steps to enhance the contrast of the image and remap their intensity values to the natural dynamic range.*

**Key-words:** Segmentation, Brain Tumor, Magnetic Resonance Imaging (MRI), Enhancement.

### 1. Introduction

The structure of the brain is very complex, and it can be viewed as a kernel section within the body. Removing the noise of an image is the main task in imaging applications. Regularly, noise removal has a resilient influence on the main elements of the image processing system. The major problem in medical field images is noise which is a random signal developed by electronic instruments. To understand the noise level in an image, one needs to know the desired amount of data and undesired noise in MRI images. MRI imaging method can give whole information about the physical body and internal view. Computer Tomography (CT) and

Positron Emission Tomography (PET) are the different methods available in present days for medical imaging applications. So improving the quality of MRI images is necessary to detect the problems effectively.

Histogram equalization (HE) is an extremely used image enhancement technique because of its simplicity and compatibility in performance [1,2]. In [3], the author has proposed a nonlinear function for modifying the histogram of the image to enhance the image's quality. In [4], the author proposed the specimen tilting method and transmission of information theory to improve the image's quality. In [5] author has been developed a new algorithm that adds the methods of histogram equalization and median filtering; the author proposed a modified version that is highlight filter in [6]. It uses the same concepts of median filter and HE, but it uses a fully automated filter for large size of images. In [7] proposed a new method, which is selective gray-level grouping. It involves grouping all histogram elements of the image into different parts. In [8] proposes a new method recursive sub-image HE is histogram-based gray level using cumulative probability density function.

In [9] author has developed an exponential contrast stretching method, in which the original image is rescaled for the appropriate resulting of the histogram of the image. In this method, modification of histogram is gained by using exponential transform, and finally, a linear function is applied to stretch contrast of output image. A Rayleigh-based contrast enhancement method which results in rescaling of the histogram of an image by Rayleigh method and modified contrast stretching algorithm, has been proposed in [10].

In [11] author proposed a new enhancement algorithm that uses special morphological operators, and it extracts the features of the image by multiscale structure elements. It is a new method that gains the desired enhancement by using specialized morphological operators. This technique is achieved by extracting the input image features based on multiscale structuring elements that produce desired output images. In [12] author has been proposed an improved dynamic range histogram modification method to stretch the range of histograms of an image.

In [13] author has introduced the sub-blocking multiple peaks HE method, in which input image is sampled and normalized to acquire local information. Later image is divided into sub-blocks, and the histogram is computed for every block for equalization. Later a specific convolution method has been used to distribute luminance values of the input image for producing desired output image. Most of the authors have been used the histogram equalization technique to improve the quality of an image which results in over enhancement in some pixels of an image. In this paper author proposed two-step regularization and mapping techniques to enhance the quality of MRI images.

## 2. Proposed Methodology

The contrast equalization method was originally proposed for a face recognition system by [14]. In this method, input image intensities have been properly rescaled to produce an acceptable contrast and brightness of an image. To achieve this a two-step regularization process is used to regularize low-quality input MRI image intensities. To achieve this process, equations 1 and 2 are used, respectively.

$$M(i,j)=\frac{K(i,j)}{(\text{mean}(|K(i',j')|^{\alpha}))^{1/\alpha}} \quad (1)$$

$$N(i,j)=\frac{M(i,j)}{(\text{mean}(\min(\beta, |M(i',j')|^{\alpha}))^{1/\alpha}} \quad (2)$$

Where  $K(i,j)$  represents the input image,  $i$  and  $j$  represents the spatial coordinates,  $K(i',j')$  represents the transpose of the input image,  $M(i,j)$  represents the resulting image of the first regularization process,  $M(i',j')$  represents the transpose of  $M(i,j)$ ,  $N(i,j)$  represents the resulting image of second regularization process,  $\alpha$  represents compressive exponent which reduces the effect of high values and  $\beta$  represents the threshold value that truncates the high values after the first step of regularization process. The values of  $\alpha$  and  $\beta$  default as 0.1 and 10, respectively. The resultant image of the regularization process has an acceptable scale, but it can still have high values. So, a nonlinear mapping function which is a hyperbolic tangent-based function is used to decrease the influence of such high values to increase the contrast and brightness of the image. The hyperbolic tangent function is calculated using equation 3.

$$U(i,j)=\beta \tanh\left(\frac{N(i,j)}{\beta}\right) \quad (3)$$

Where  $U(i,j)$  represents the desired result of the input degraded image, due to default values of  $\alpha$  and  $\beta$  are resulting input image black at some pixel areas so these values should be changed to acquire the acceptable desired image. These values are replaced by  $\mu$  in both Equations 1 and 2. The parameter  $\mu$  value should always greater than zero. The higher value of  $\mu$  gives better-enhanced results, while the lower values give degradation in desired results. The value of  $\mu$  should be modified till the desired output is acceptable in contrast and brightness. The modified regularization process is calculated by utilized equations 4 and 5, respectively.

$$M(i,j)=\frac{K(i,j)}{(\text{mean}(|K(i',j')|^{\mu}))^{1/\mu}} \quad (4)$$

$$N(i,j)=\frac{M(i,j)}{(\text{mean}(\min(\mu, |M(i',j')|)^\mu))^{1/\mu}} \quad (5)$$

A new mapping process of two steps has been implemented instead of equation 3 to decrease the extremely high values. In this two-level mapping process, image intensity values are remapped in a linear and nonlinear manner. The first step includes a nonlinear function that uses MSLF (modified standard logistic function) to improve the image's contrast. The CSLF (conventional standard logistic function) is computed utilizing equation 6 [15].

$$H(i,j)=\frac{\exp(N(i,j))}{1+\exp(N(i,j))} \quad (6)$$

Where  $H(i,j)$  is the output image results from the conventional standard logistic function. In this paper, MSLF is used over CSLF for more improvement in the brightness and contrast of an image. The modified CSLF function with the power of  $\mu$  is shown in equation 7.

$$\hat{H}(i,j)=\left(\frac{\exp(N(i,j))}{1+\exp(N(i,j))}\right)^\mu \quad (7)$$

Where  $\hat{H}(i,j)$  represents the resultant image of the MSLF function. To achieve the desired output image, the result of the equation 7 is normalized by remapping intensities of the image with a dynamic range, which is the second step of the two-level mapping process. This can be processed using equation 8 [16].

$$P(i,j)=\frac{\hat{H}(i,j)-\min(\hat{H}(i,j))}{\max(\hat{H}(i,j))-\min(\hat{H}(i,j))} \quad (8)$$

Where  $P(i,j)$  is the final enhanced MRI image.

### 3. Results and Discussions

Figure 1-5 represents the original MRI image and enhanced image with  $\mu$  value as 1.2, 2.4 and 3.6, respectively. Five test images are taken into consideration to analyze the performance of the proposed enhancement algorithm. From the figures, we can observe that the higher value of  $\mu$  gives better enhancement results in the output image.

Figure 1 - (a) Original Test Image 1, Enhanced Image at (b)  $\mu=1.2$ , (c)  $\mu=2.4$  and (d)  $\mu=3.6$

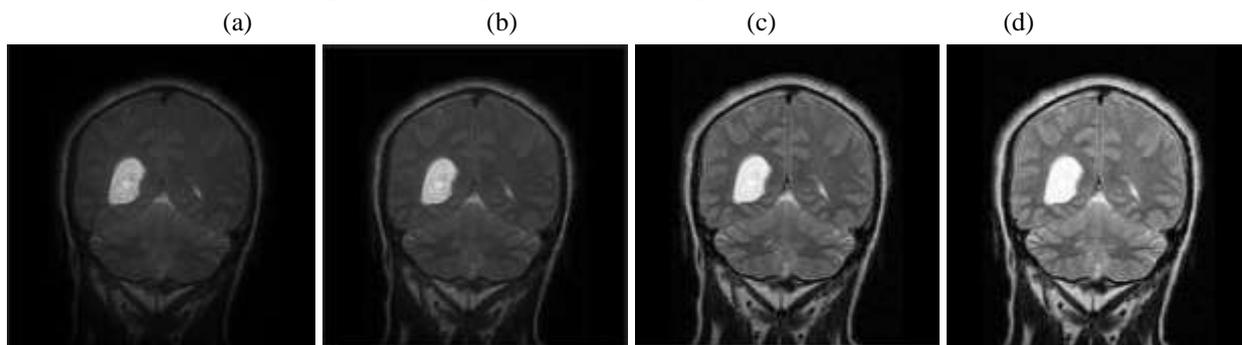


Figure 2 - (a) Original Test Image 2, Enhanced Image at (b)  $\mu=1.2$ , (c)  $\mu=2.4$  and (d)  $\mu=3.6$

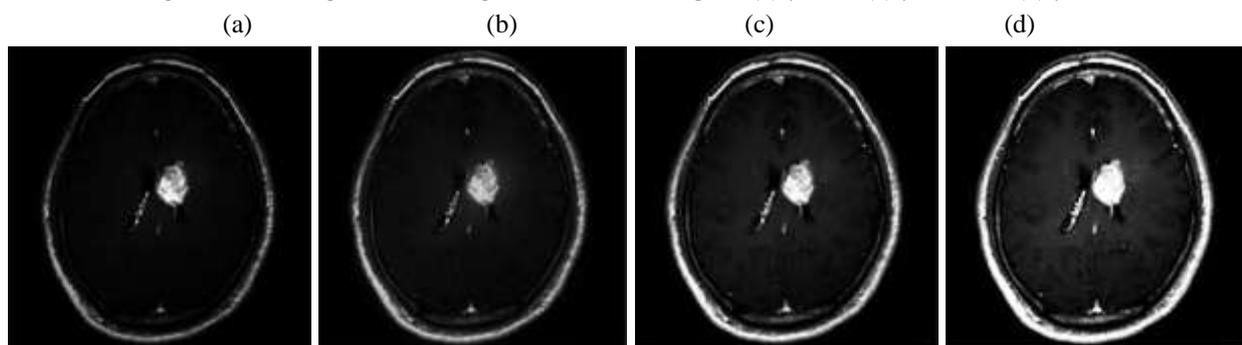


Figure 3 - (a) Original Test Image 3, Enhanced Image at (b)  $\mu=1.2$ , (c)  $\mu=2.4$  and (d)  $\mu=3.6$

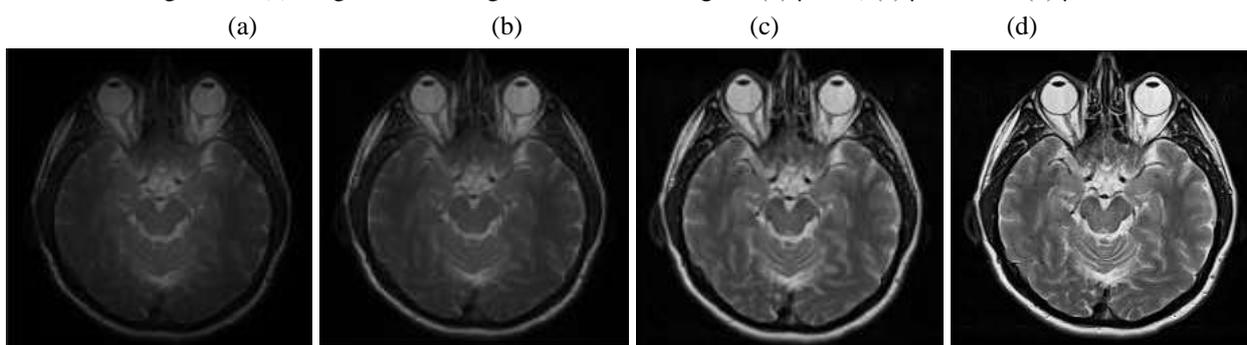


Figure 4 - (a) Original Test Image 4, Enhanced Image at (b)  $\mu=1.2$ , (c)  $\mu=2.4$  and (d)  $\mu=3.6$

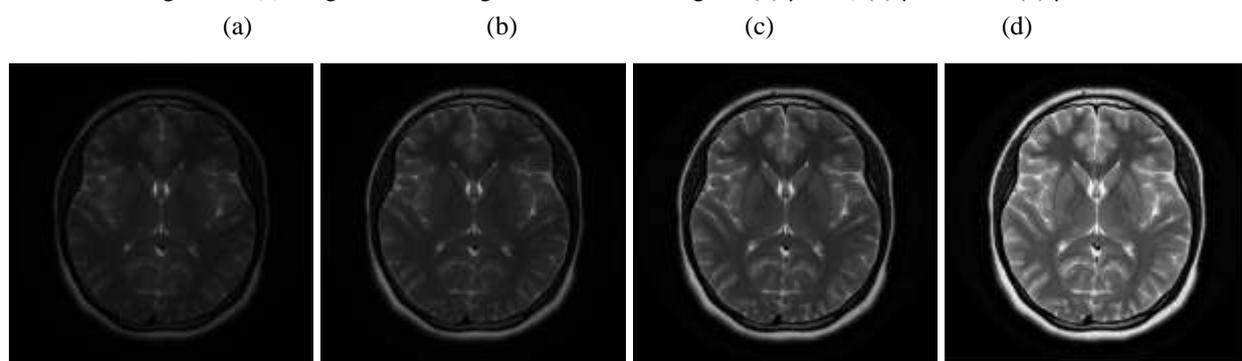
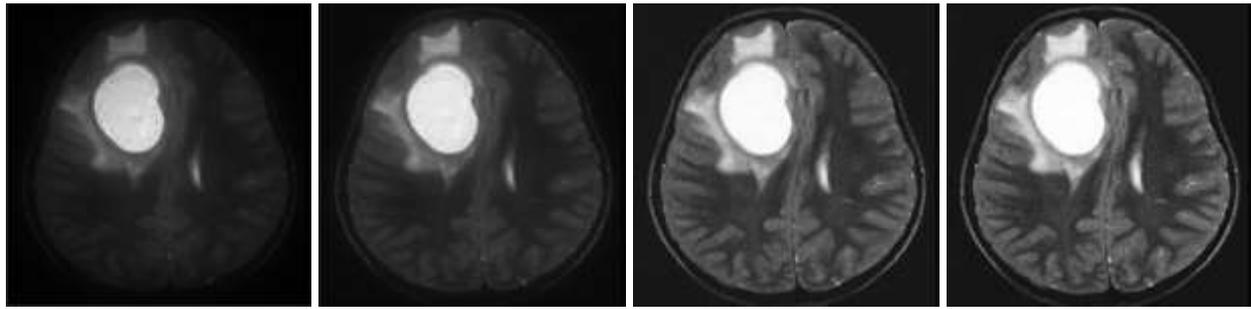


Figure 5 - (a) Original Test Image 5, Enhanced Image at (b)  $\mu=1.2$ , (c)  $\mu=2.4$  and (d)  $\mu=3.6$



Peak Signal to Noise Ratio (PSNR) is a highly used quality measure for analyzing the quality of an image. Higher PSNR values determine the higher quality of the output image. Also, PSNR is calculated from the equation of mean square error (MSE),

$$MSE = \frac{1}{PQ} \sum_{j=0}^P \sum_{k=0}^Q (M_{jk} - N_{jk})^2 \quad (9)$$

Where  $X_{jk}$  input image and  $Y_{jk}$  output image. The empirical result proves AR-ESIHE has a low MSE value among all other existing methods.

PSNR plays the main role in analyzing the quality of an image. A higher PSNR value means image enhancement is efficient. It is estimated in decibels (dB) and is defined as,

$$PSNR = 10 \log_{10} \left( \frac{R^2}{MSE} \right) \quad (10)$$

Entropy gives the amount of data in an image. The high entropy value shows the high quality of an image. It can be expressed as, Where  $P_j$  is the probability of getting an intensity value. The empirical result shows IME has High entropy value compare to existing methods.

$$Entropy = - \sum_{j=1}^l P_j \log_2(P_j) \quad (25) \quad (11)$$

Where  $P_j$  is the probability of getting an intensity value. The empirical result shows IME has High entropy value compare to existing methods.

Table 1 - Comparison of MSE Values of the Test Images

Test images	MSE			
	Original image	Enhanced image		
		$\mu = 1.2$	$\mu = 2.4$	$\mu = 3.6$
Image 1	85.661	53.576	53.555	17.683
Image 2	84.116	53.024	53.093	18.772
Image 3	84.437	53.426	53.365	18.974
Image 4	85.340	54.444	54.411	18.532
Image 5	79.203	50.311	50.224	18.905

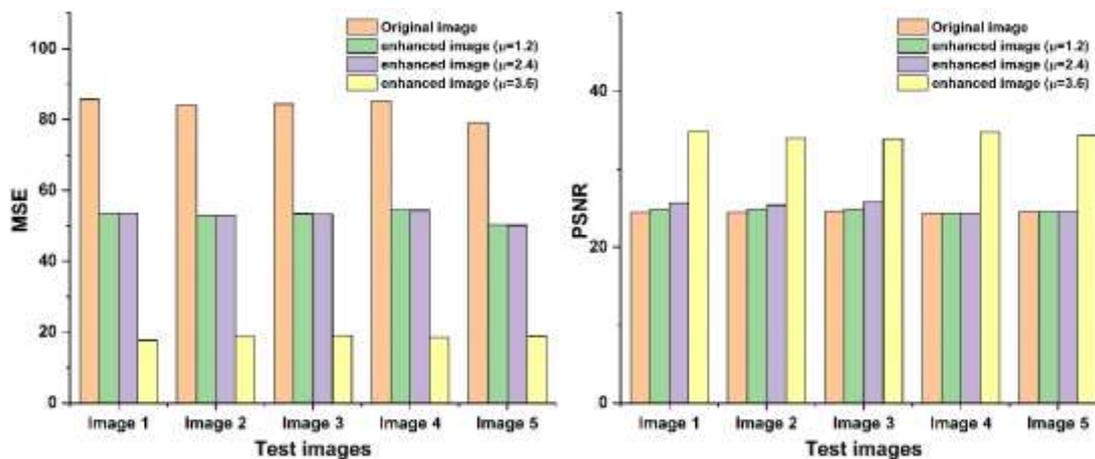
Table 2 - Comparison of PSNR Values of the Test Images

Test images	Original image	Enhanced image		
		$\mu = 1.2$	$\mu = 2.4$	$\mu = 3.6$
Image 1	24.430	24.936	25.689	34.856
Image 2	24.453	24.889	25.389	33.991
Image 3	24.550	24.896	25.823	33.894
Image 4	24.326	24.326	24.326	34.756
Image 5	24.578	24.578	24.578	34.350

Table 3 - Comparison of Entropy Values of the Test Images

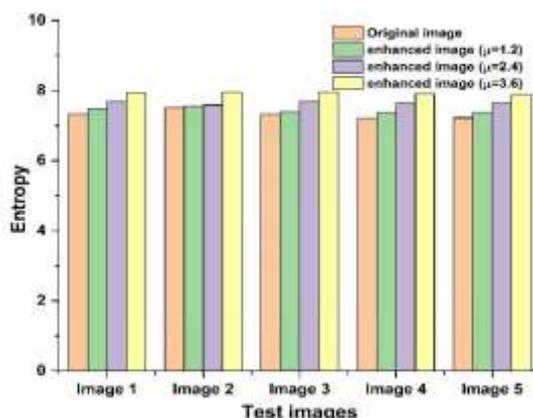
Test images	Original image	Enhanced image		
		$\mu = 1.2$	$\mu = 2.4$	$\mu = 3.6$
Image 1	7.334	7.483	7.678	7.934
Image 2	7.514	7.558	7.586	7.952
Image 3	7.318	7.397	7.694	7.953
Image 4	7.212	7.371	7.632	7.903
Image 5	7.222	7.371	7.638	7.887

Figure 6 - Comparison of Values for Input Image and Output Image (a)MSE, (b) PSNR, and (c) Entropy



(a)

(b)



(c)

Table 1-3 represents the values of the MSE, PSNR and entropy values of the original image and enhanced image with different  $\mu$  values. Figure 6 shows the graphical representation of tabular values of MSE, PSNR and Entropy. From the figures, it is evident that the MSE value for the enhanced image with  $\mu=3.6$  is low as compared with the original degraded image and enhanced output image with  $\mu=1.2$  and  $\mu=2.4$ . And it is also evident that the PSNR value of the enhanced image with  $\mu=3.6$  is high as compared with the original image and enhanced image with  $\mu=1.2$  and  $\mu=2.4$ . The entropy value of the output image with  $\mu=3.6$  is low as compared with the original image and enhanced output image with  $\mu=1.2$  and  $\mu=2.4$ .

#### 4. Conclusion

In this Present paper, a contrast enhancement technique with two-step regularization and two-step mapping processes for MRI brain images has been proposed. Here the two-step regularization process is involved in regularization of higher intensity values by using a modified threshold value  $\mu$ . A higher  $\mu$  value gives more improved contrast and brightness of an image. The two-step mapping process involves in remap the intensity values of the image to achieve desired output image. MSE, PSNR and entropy values have been calculated to know the better value of  $\mu$  for the desired output image. The mean square error value is less at  $\mu=3.6$  as compared with other  $\mu$  values and input MRI image. As MSE and PSNR are inversely proportional to each other PSNR value for the enhanced image at  $\mu=3.6$  is low as compared with other  $\mu$  values and the input image. The entropy value also high at  $\mu=3.6$  as compared with other  $\mu$  values and original image.

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