Image Enhancement of Human Brain Magnetic Resonance Images (MRI) using Logarithmic Transform Coefficient Histogram Matching

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1. Introduction

Image enhancement technology provides a vital role in image processing. It is a technique which reduces image noise, removes artefacts, and protect details. Its reason is to increase certain image highlights for analysis, diagnosis and display. The method can be performed by either suppressing the noise or increasing the image contrast.[1] Moreover, there are two wide categories of picture improvement procedures. They are spatial space techniques for direct control of image pixels and frequency domain techniques for control of Fourier transform or wavelet transform of an image. The histogram of a picture appears us the dissemination of grey levels within the picture enormously valuable in picture processing or other words the image histogram gives a worldwide description of the visual appearance of the image.[2]

Histogram processing is a technique for various applications, such as in picture normalization and enhancement, object recognition and visible watermarking. For a uniform target histogram, we talk about histogram equalization. Histogram Equalization is a technique to process the digital images for contrast picture improvement. [3] On the other hand, the histogram matching or histogram specification is a process where a time series, picture, or higher measurement scalar data is adjusted such that its histogram matches that of another (reference) dataset. [4]

In case of transform domain improvement procedures, the image intensity data are mapped into a given transform domain by employing a transform such as 2-D discrete cosine transform (DCT), Fourier transform and other fast unitary transforms. The essential thought of utilizing this method is to improve the picture by manipulating the transform coefficients.[5]

In this report, we implement the logarithmic transform coefficient histogram matching, which employments the fact that the connection between stimulus and perception is logarithmic. The performance of the algorithm is compared quantitatively to traditional histogram equalization utilizing the Mean Absolute Error (MAE). Finally, we present a number of results over some human brain Magnetic Resonance Images (MRI) are displayed to demonstrate the performance of the proposed algorithm alongside traditional histogram equalization.

2. State-of-the-art Review

In this section, we present some state-of-the-art histogram matching techniques, which have been utilized in researches for medical images enhancement.

Particularly, Foisal Hossain et al.,[6] have proposed a modern strategy of medical image enhancement based on the nonlinear method and logarithmic transform coefficient histogram specification that moves forward the visual quality of digital pictures as well as pictures that shows dark shadows due to restricted dynamic range of imaging. These methods demonstrated a capable method for image improvement and was investigated the execution compared to the histogram equalization method.

Then, Xiaofei Sun et al., [2] have proposed a modern histogram normalization method to decrease the intensity variation between MRIs obtained from diverse acquisitions. The method can normalize scans which were procured on diverse MRI units and the researchers demonstrate that the method can enormously enhance picture investigation performance.

In the continue, Amod Jog et al., [8] have proposed a data-driven approach to image synthesis. The synthesis transformation is done on picture patches by a trained bagged gathering of regression trees. Also, validation is done by synthesizing T2-weighted contrasts from T1-weighted scans, for apparitions and real data.

Then, Sereyed Pooya Ehsani et. al., [9] have proposed an adaptive and iterative histogram matching (AIHM) algorithm for chromosome contrast enhancement, particularly in banding designs. The reference histogram, with which the initial picture should be matched, is made based on a few processes on the initial image histogram. Utilization of raw data within the histogram of the initial image had come about in more reliance on the input image, procuring superior contrast enhancement.

Finally, Lazlo G. Nyúl et al. [10] have proposed a two-step method wherein all pictures can be changed for the same protocol and body region and the transformed pictures comparable power will have comparative tissue meaning. Also, standardized pictures can be shown with settled windows without the required for per-case adjustment.

By large, the results of researches indicate that the histogram matching method shows the best results in terms of the enhancement of the medical images.

3. Background

In this section, description about necessary background is given so that the proposed method can be understood easily.

3.1 Fast Fourier Transform (FFT)

A fast Fourier transform (FFT) is an algorithm that computes the discrete Fourier change (DFT) of a sequence, or its inverse (IDFT). Fourier examination converts a signal from its original domain (regularly time or space) to representation within the frequency domain and vice versa. The DFT is gotten by decomposing a sequence of values into components of diverse frequencies. This operation is valuable in numerous areas, but computing it specifically from the definition is frequently as well moderate to be practical. An FFT quickly computes such transformations by factorizing the DFT matrix into an item of sparse (for the most part zero) variables. The DFT is characterized by the equation:[11]

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi kn/N} \qquad k = 0, \ldots, N-1,$$

where $e^{i2\pi/N}$ is a primitive Nth root of 1.

3.2 Logarithmic Transform

The logarithmic transform assists us to appear the frequency content of an image. This transformation maps a narrow range of low grey level values within the input picture into a wider range of the output level. The inverse is true of higher values of input level. This sort of change is utilized to extend the values of dark pixels in a picture whereas compressing the higher-level values. Be that as it may, the histogram of this data is ordinarily compact and uninformative. The connection between stimulus and perception is logarithmic. Log transformation is done in two steps. The primary step requires the creation of a matrix to preserve the stage of the transformed picture. This will be utilized afterwards to inverse the stage of the transform coefficients. In the second step, the logarithm is taken on the modulus of the coefficients according to the following equation:[12]

$$\hat{X}(i,j) = \ln\left(\left|X(i,j)\right| + \lambda\right)$$

where λ is a shifting coefficient, usually set to 1.

3.3 Histogram Equalization

Histograms are the premise for various picture processing methods. Histogram equalization maps the input image's intensity values so that the histogram of the resulting picture will have roughly uniform dissemination. The variable r represents the grey level of a picture to be improved, T is the transformation function and s is the transformed value. At that point, s can be represented as:[13]

$$s = T(r) = \int_0^r p_r(w)\,dw$$

If p_r and p_s represents the probability density function of r and s respectively then Ps can be obtained by applying a simple formula:

$$p_s(s) = p_r(r)\left|\frac{dr}{ds}\right|$$

Given a transformation function T(r) we are able to get p_s so that $p_s(s)$ follows nearly uniform dispersion which results in histogram equalized picture.[14]

3.4 Histogram Matching

Histogram matching or specification, a more generalized form of histogram equalization, permits us to change the data so that the resulting histogram matches a few desired curves. The main procedure of histogram mapping lies at solving a formula that compares the integrals of the probability density function, essentially comparing their cumulative density functions: [9]

$$\int_0^{n_B} p_B(y)dy = \int_0^{n_A} p_A(x)dx$$

where, $p_B(n_B)$ is our anticipated hyberbolization of our histogram, $p_A(n_A)$ and is our original histogram, which we will estimate as an exponential:

$$p_A(n_A) = A_0 e^{-n_A}, \quad p_B(n_B) = B_0 n_B e^{-n_B^2}$$

Combining the integral equation and solving we get:

$$B_0 \int_0^{n_B} y e^{-y^2} dy = A_0 \int_0^{n_A} e^{-x} dx$$

$$B_0 \left(\frac{1 - e^{-n_B^2}}{2} \right) = A_0 \left(1 - e^{-n_A}\right)$$

$$n_B = \sqrt{-\ln\left(1 - \frac{2A_0}{B_0}\left(1 - e^{-n_A}\right)\right)}$$

The resulting equation is the transformation of exponential dissemination to a hyberbolization of that histogram. A common usage of this common histogram mapping strategy is wiped out three steps:

1) equalizing the original image,
2) histogram equalize the anticipated output image and

3) apply the inverse of the second transformation to the original equalized image.

$$T_1 = F_A(n_A) = \int_0^{n_A} p_A(y)dy$$

$$T_2 = F_B(n_B) = \int_0^{n_B} p_B(x)dx$$

$$T = T_2^{-1}(T_1(n_A))$$

Since the data are discrete, it will be nearly impossible to produce an impeccably flat or impeccably matched histogram.

3.5 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) measures the average size of the errors in a set of predictions, without considering their direction. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight:[15]

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n} |y_j - \hat{y}_j|$$

MAE can range from 0 to ∞ and are indifferent to the direction of errors. It is a negatively-oriented score, which means lower values are better.

4. Implementation

In this section, we explain the implementation of the logarithmic transform coefficient histogram matching. This method is a straightforward and efficient strategy of image enhancement. Figure (1) appears the block diagram of our proposed method:

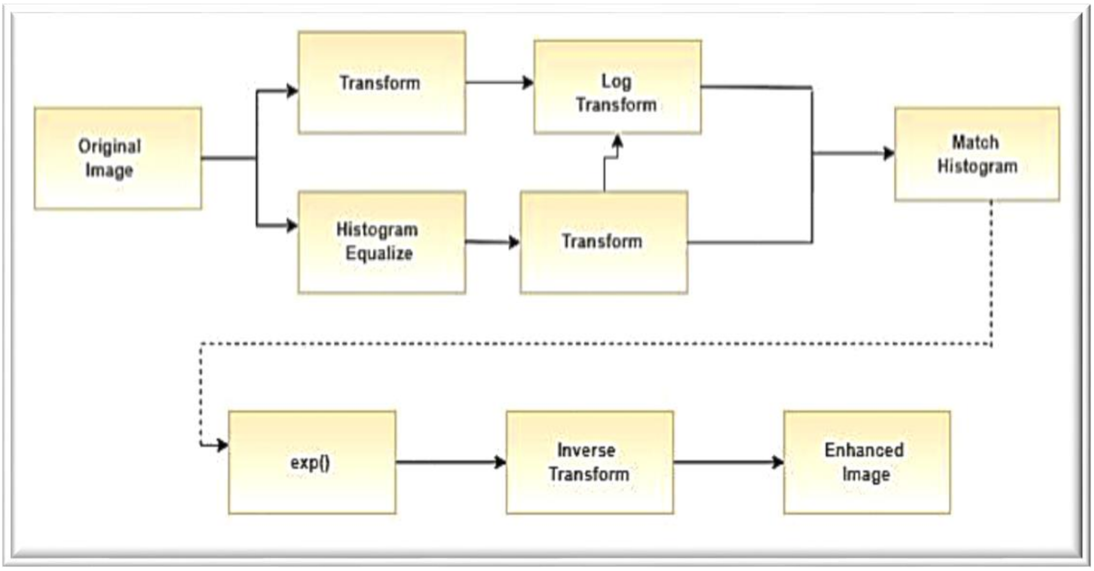


Figure 1: Block Diagram of Logarithmic Transform Histogram Matching

This method employments the following steps:

Input: **Original Image**
Step 1: **Transform Image (Fourier)**
Step 2: **Equalize the Histogram of the Image**
Step 3: **Take logarithm of magnitude coefficients**
Step 4: **Calculate coefficient histogram**
Step 5: **Take logarithm of original transform data**
Step 6: **Map data to equalized histogram**
Step 7: **Exponentiate data**
Step 8: **Inverse Transform**
Output: **Enhanced Image**

Particularly, the proposed method inputs an image and apply Fast Fourier Transform (FFT), which includes mapping the intensity data into the given transform. In the second step, logarithmic transformation is connected to the magnitude of FFT values which makes the histogram informative. In this step, the phase of the transformed image is preserved by making a matrix which is able to be used later to restore the phase of the transform coefficients. [6] In parallel with this, histogram equalization depicted in section 3.3 is applied to the original picture. FFT transform is applied to the histogram equalized image. At that point, the logarithmic transformation is applied to the magnitude of FFT transformed values. In the next step, we ought to match the transformed data of the original picture to the transformed data of the histogram equalized image by utilizing histogram mapping. At that point, the matched information is exponentiated and already isolated phase is restored. Within the final step, the inverse IFFT transform is applied which gives the output improved image. By mapping the picture to the histogram equalized histogram and returning the data to the spatial domain, the dynamic range of the image has been extended, contrast and detail will be enhanced throughout the image.[12]

Typically, the basis for our investigations of transform histograms and histogram equalization, a spatial strategy that suffers from extraordinary dynamic range expansion, which can result in ugly artefacts. By combining this fundamental method with transform histogram matching improvement strategies, the end results can be shockingly way better in visual quality and quantitative estimation.

4. Experimental Results

We have proposed a method of MR images enhancement which demonstrated an effective strategy for image enhancement. This method was explored to appear the performance compared to the histogram equalization procedure. A sample of proposed method compared with histogram equalization, is below (figure 2):

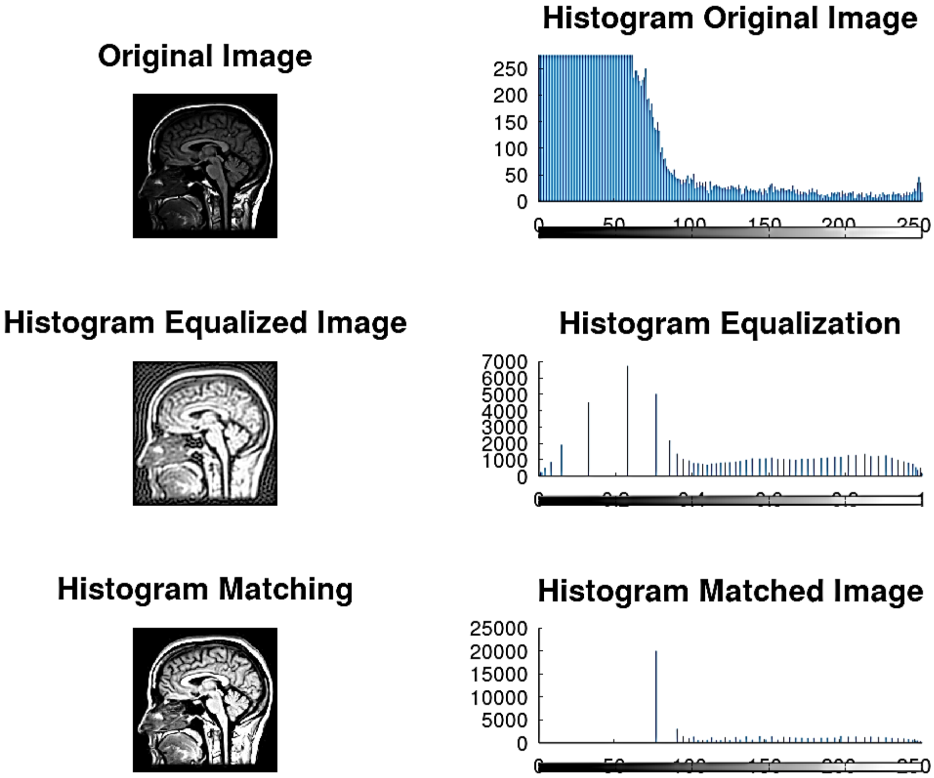
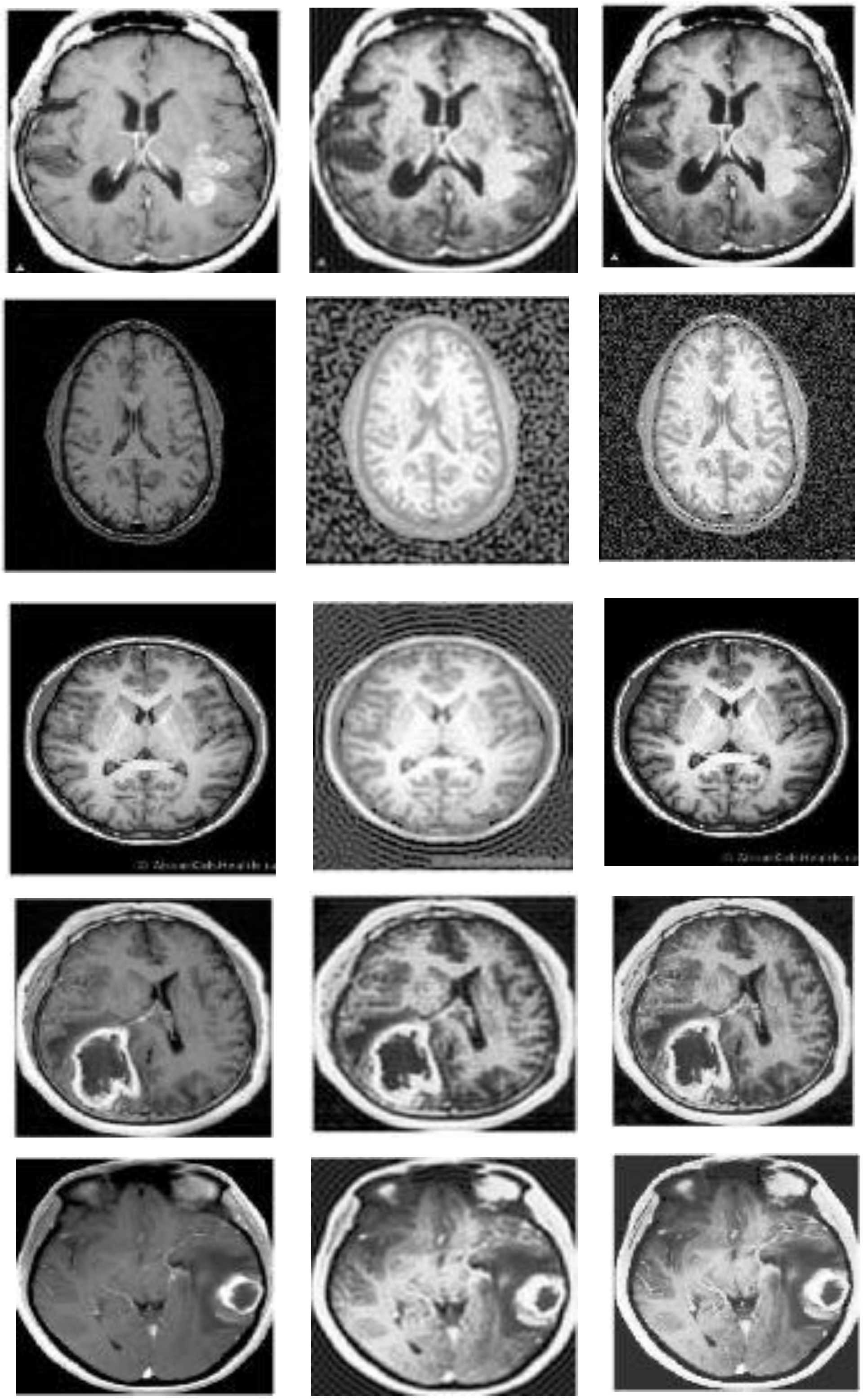


Figure 2: An Example Log Transform Histogram Matching

Moreover, eight MR images have been used as appeared in figure 3 below, which were taken by a free online medical database[16]:



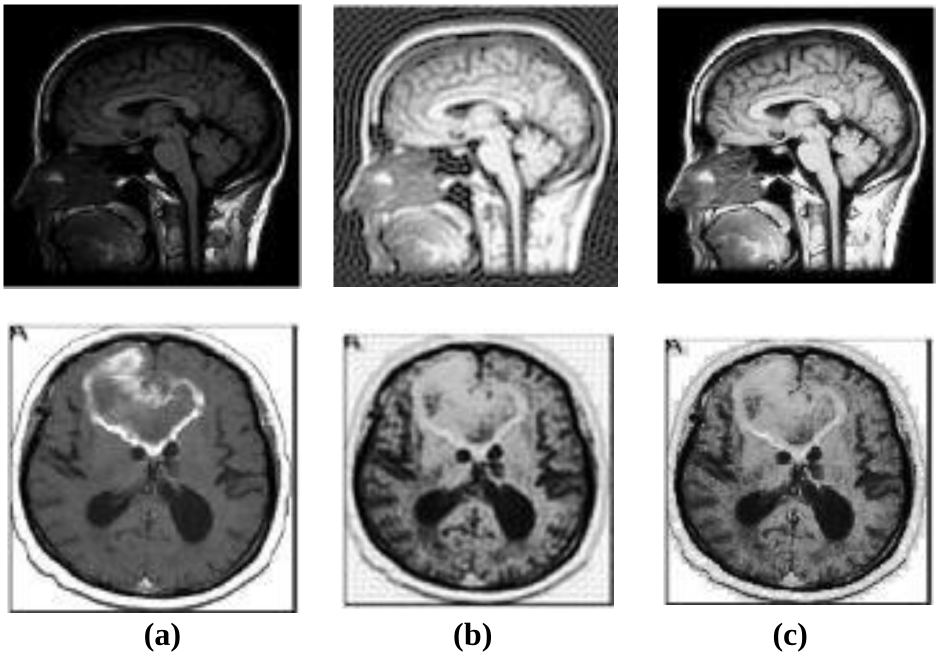


Figure 3: a) Original Image, b) Histogram Equalized Image, c) Image with Proposed Method

This figure appears the visual assessment of the proposed method compared to the histogram equalization method. Exploring figure 3 (a), (b) and (c) separately, it can be seen that the proposed method gives a better result for the image enhancement than generalized histogram equalization method. In figure 3(c) it can be seen the visual quality of digital pictures, as well as the pictures that show dark shadows due to the restricted dynamic range of imaging, has been improved.

Table 1: Comparison of AME of the Histogram Equalized Image with the Proposed Method

Image	Histogram Equalized	Proposed Method
Image 1	0.29196	0.26002
Image 2	0.51171	0.07036
Image 3	0.44209	0.09617
Image 4	0.29704	0.28678
Image 5	0.42991	0.07223
Image 6	0.33013	0.18m 868

Image 7	0.43788	0.10865
Image 8	0.49330	0.07757

Table (1) gives quantitative measure of image enhancement with respect to AME as a measure of error. From table (1), it can also be observed that the image 2, after histogram equalization the AME is 0.51171. Using the proposed method, the EME value decreases to 0.07036, that is lower than other.

5. Discussion

This paper proposed a strategy of medical image enhancement based upon the logarithmic transform coefficient histogram equalization utilizing AME as a measure of performance. The performance of this algorithm was compared to a classical histogram equalization enhancement technique. This method enhances the visual quality of pictures that contain dark shadows due to the restricted dynamic range of imaging. Experimental results discover that the proposed technique outperform commonly utilized enhancement strategy like the histogram equalization qualitatively and quantitatively. The proposed strategy can also allow excellent results in image enhancement utilizing real pictures. In the future work, it can be utilized to enhance images in such a way that within the resultant pictures face becomes clearer than the original and can be utilized further to face recognition purpose.

6. References

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