

Contrast Enhancement of brain MRI images using histogram based techniques

Pratik Vinayak Oak¹, Prof.Mrs.R.S.Kamathe²

ME (Signal Processing), PES's Modern College of Engineering, Pune¹

Assistant Professor, E &TC Dept. PES's Modern College of Engineering, Pune²

Abstract— MRI is an advanced medical imaging technique used to produce high quality images of human body and different parts. It gives detail information to analyse the diseases. Medical image processing plays important role to give information in more extent for such advance images. Original MRI images are generally having low contrast. It is difficult for doctors to analyse them. By increasing the contrast of an image, it will be easy for analysing because of detailed information. This increase in contrast can be done by number of ways in image processing. This paper compares different methods of enhancement of brain MRI using histogram based techniques.

Keywords— brain MRI, medical image processing, enhancement, histogram

I. INTRODUCTION

Magnetic resonance imaging (MRI) provides detailed images of living tissues, and is used for both brain and body human studies. Data obtained from MR images is used for detecting tissue deformities such as cancers and injuries[7].MRI imaging is also used when treating brain tumor, ankle and foot. From these high-resolution images, we can derive detailed anatomical information to examine human brain development and discover abnormalities. MRI consists of T1 weighted, T2 weighted and PD (Proton Density) weighted images [6].

To give proper diagnosis and good results, doctors are provided with the different results of enhanced images. Enhancement is a fundamental task in digital image processing and analysis, aiming to improve the appearance of image in terms of human brightness perception. Contrast enhancement is among them and is often part of image processing systems in the pre-processing and/or post-processing stage [8].

The classical contrast enhancement is Histogram Equalization (HE), which has good performance for ordinary images, such as human portraits or natural images. Transformation or mapping of each pixel of input image into corresponding pixel of processed output image is called 'Histogram Equalisation'[8]. It considers probability of occurrence of every gray level in entire image and gives output image having same size as input. Same concept of histogram is used in this paper for brain MRI images. But here some additional techniques related to histogram are used to remove drawbacks of previous methods and give proper contrast for further processing.

This paper is organised as follows: In section II, details of different histogram based enhancement methods is presented with their mathematical equations. In section III, details of quality measures used is provided with significance. In section IV, observed results are given for brain MRI images with respective histograms. Results are objectively assessed with different quality measures for contrast.

II. METHODOLOGY

Histogram Equalisation (HE) and their advanced methods are considered for contrast enhancement of images.

2.1 Histogram Equalisation (HE) [8]

Consider a digital image with gray levels in the range $[0, L - 1]$, Probability Distribution Function of the image can be computed as :

$$P(r_k) = \frac{n_k}{n}, k = 0, \dots, L - 1$$

where r_k is the k^{th} gray level and n_k is the number of pixels in the image having gray level r_k . Cumulative Distribution Function (CDF) can also be computed as followed:

$$C(r_k) = \sum_{i=0}^k P(r_i), k = 0, 1, \dots, L - 1$$

HE appropriates gray level s_k to gray level r_k of the input image using CDF. Finally, transformation function to be applied on entire is:

$$S_k = (L - 1) * C(r_k)$$

Histogram Equalization (HE) method has two main disadvantages which affect efficiency of this method. These two main disadvantages are followed:

- 1) Histogram Equalization (HE) assigns one gray level into two different neighbour gray levels with different intensities.
- 2) If most of an image includes a gray level, Histogram Equalization (HE) assign a gray level with higher intensity to that gray level and it gives washed out appearance to the resultant image [1].

Bi-Histogram Equalisation (BHE) is one of the ways of getting better results.

2.2 Bi-Histogram Equalization (BHE)



BHE first finds average point in histogram of the image i.e. mean of image and then divides histogram to two segments based on this point. After that, histogram equalization operation is applied on each segment separately. There are two cumulative distribution functions for two segments. Gray level (rk) under the average point is pointed to the new gray level (Sk) by:

$$S_k = (L1) * C1(rk)$$

CDF for same image below average point is calculated as:

$$C1(rk) = \frac{\sum_{i=0}^k n_i}{\sum_{j=0}^{L1} n_j}; k = 0, 1, \dots, L1$$

where L1 is entropy, calculated as:

$$L1 = \sum_{k=0}^{L-1} P(rk) * rk$$

Similarly, gray levels above mean are transformed to new levels by function Sk as:

$$S_k = (L - 1 - L1) * C2(rk) + L1$$

CDF for this is given as:

$$C2(rk) = \frac{\sum_{i=L1+1}^k n_i}{\sum_{j=L1+1}^{L-1} n_j}; k = L1 + 1, \dots, L1$$

Two transformation functions are separately applied on image to get final image with same size [2].

In BHE, due to consideration of average point in histogram, there is drastic change in number of pixels above & below that point. Improvement over this is suggested by Ali Ziaei et al. as “modified BHE”.

2.3 Modified BHE [1]

This method first finds a grey level with maximum number of pixels in an image. Then around this level, average of number of pixels is taken and replaced for every pixel. This is done in both sides of that level. Probability of occurrence of new values is calculated and sum is taken. Then every probability is adjusted to get sum of probabilities should be equal to 1 by adding or subtracting some constant difference with respect to 1. The new PDF is then applied on image for equalisation.

Sometimes, that maximum occurred grey level may be present in background. So to avoid undesirable effect, three separate images are observed as: only averaging in left of level, only in right of level and both directions. Best of three images is chosen as output.

This method avoids quick change in number of pixels corresponding to grey levels [1]. To preserve average brightness of an image, one more method is suggested by Yeong-Taeg Kim as “brightness preserving BHE”.

2.4 Brightness preserving BHE (BBHE) [2]

The BBHE firstly decomposes an input image into two sub-images based on the mean of the input image. One of the sub-images is the set of samples less than or equal to the mean whereas the other one is the set of samples greater than the mean. Then the BBHE equalizes the sub-images independently based on their respective histograms such that one of the sub-images is equalized over the range up to the mean and the other sub-image is equalized over the range from the mean based on the respective histograms. Thus, the resulting equalized sub-images are bounded by each other around the input mean, which has an effect of preserving mean brightness [2].

Denote by X_m the mean of an image X and assume that $X_m \in [X_0, X_1, \dots, X_{L-1}]$. Based on the mean, the input image is decomposed into two sub-images X_l and X_u as

$$X = X_l \cup X_u$$

Where

$$X_l = \{X(i,j), X(i,j) \leq X_m, \forall X(i,j) \in X\}$$

And

$$X_u = \{X(i,j), X(i,j) > X_m, \forall X(i,j) \in X\}$$

Next, respective probability density functions of sub-images are defined as:

$$P_l(X_k) = \frac{n_{kl}}{n_l}; k = 0, 1, \dots, m$$

And

$$P_u(X_k) = \frac{n_{ku}}{n_u}; k = m + 1, \dots, L - 1$$

Where the numerators are respective number of grey levels in lower and upper images respectively. The sum of denominators is nothing but total number of pixels in an image. The respective CDF's are given as:

$$C_l(x) = \sum_{j=0}^k P_l(X_j)$$

And

$$C_u(x) = \sum_{j=m+1}^k P_u(X_j)$$

Similar to HE, a new transformation functions for lower and upper images are defined as:

$$F_l(x) = X_0 + (X_m - X_0) * C_l(x)$$

And

$$F_u(x) = X_{m+1} + (X_{L-1} - X_{m+1}) * C_u(x)$$



Finally, based on these functions, sub-images are equalised independently and combined to form the resultant image as output of BBHE [2].

The methods used above are global or less partition based. But there is another approach for histogram based technique given as local enhancement. These methods are “Adaptive HE” and “Contrast Limited AHE”.

2.4 Adaptive Histogram Equalization (AHE)

In this method, instead of applying transformation function directly on entire image, it is applied on sub-images separately and then combined in proper manner. Steps for method are given as:

- 1) Divide the input image into an NxN matrix of sub-images.
- 2) Compute the mapping from histogram equalization (HE) of each of these sub-images.
- 3) For each pixel in the input image, do the following: [3]
 - i) If the pixel belongs to an internal region (IR), then
 - (a) Compute four weights, one for each of the four nearest sub-images, based on the proximity of the pixel to the centres of the four nearest sub-images (nearer the centre of the sub-image, larger the weight).
 - (b) Calculate the output mapping for the pixel as the weighted sum of the HE mappings for the four nearest sub-images using the weights computed above.
 - ii) If the pixel belongs to an border region (BR), then
 - (a) Compute two weights, one for each of the two nearest sub-images, based on the proximity of the pixel to the centres of the two nearest sub-images
 - b) Calculate the output mapping for the pixel as the weighted sum of the HE mappings for the two nearest sub-images using the weights computed above.
 - iii) If the pixel belongs to a corner region (CR), the output mapping for the pixel is the HE mapping for the sub-image that contains the pixel.

Apply the output mapping obtained to each of the pixels in the input image to obtain the image enhanced by AHE. [3]

With this method, most of the times “block effect” is observed in the output due to sub-image processing. This drawback is somewhat reduced by another method named as “contrast limited AHE”.

2.5 Contrast Limited Adaptive Histogram Equalization (CLAHE)

The enhancement is therefore reduced in uniform areas of an image which prevents over-enhancement of noise and reduces edge shadowing effect of unlimited AHE. Size of pixel’s contextual region and clip level of histogram are basic parameters of CLAHE [4].

More specifically, in the original CLAHE algorithm, the input gray scale image, $I_i(i, j)$ (composed of $M * N$ pixels) is initially split into rectangular regions, typically of $64 * 64$ pixels sized. Then, for each region the histogram is computed with B bins. Therefore, the generic

region (k, l) has the histogram function $H_{k,l}(s)$, with $s \in [0, B - 1]$. Then, a cut is operated limiting the histogram values to the clip-limit

$$\beta = (M * N) / (B * \alpha)$$

where $\alpha \in [0, 1]$ represents the maximum percentage of pixels allowed in a given bin. After thresholding, the pixels in excess in each bin are equally redistributed until they do not exceed β .

Then obtained histogram is then normalized and used to estimate the cumulative probability function $g_{k,l}(x)$ which is the mapping function estimated for the region of index k, l . Then the interpolation stage is done. Given P the pixel position, s the image value in P (i.e. $I(P) = s$), A, B, C, D the centre points of the neighbour contextual regions (upper-left, upper-right, lower-left, lower-right) with mapping functions $F_A(s), F_B(s), F_C(s)$ and $F_D(s)$, the value of P in the output image is s' and it is obtained using a weighted sum of the mapping functions over the four neighbour regions. Assuming that x and y are the distances between P and the segment AC and AB respectively normalized by the length of AB and AC (see 1). For each (x, y) the new value s' is given by:

$$s' = (1-y)((1-x)F_A(s) + x * F_B(s)) + y((1-x).F_C(s) + x * F_D(s))$$

At the end of this process each pixel has its own mapping function, which can be globally expressed as:

$$T(i, j, s) = (B-1) * [\text{Sum}(i=0:s) F_{i,j}(s)]$$

Where $s \in [0, B-1]$. In above equation, $F_{i,j}(s)$ represents distribution function of the pixel $I_{i,j}$ after s .

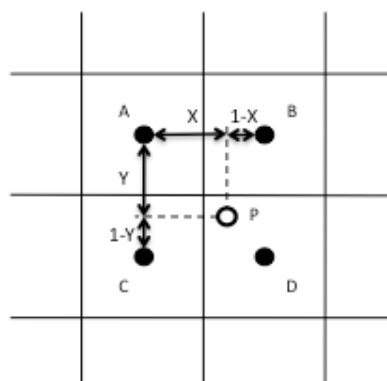


Figure 1: Bi-linear interpolation

In short, we can write steps as: Manual input N, CL (actual clipping level) [4]

- 1) Divide the input image into an NxN matrix of sub-images
- 2) For each sub-image do the following
 - 2.1) compute the histogram of the sub-image
 - 2.2) calculate the nominal clipping level, P from the actual clipping level, C using the binary search.



2.3) for each gray level bin in the histogram do the following

- (a) If the histogram bin is greater than the nominal clip level P, clip the histogram to the nominal clip level P
- (b) Collect the number of pixels in the sub-image that caused the histogram bin to exceed the nominal clip level P.

2.4) distribute the clipped pixels uniformly in all histogram bins to obtain the Renormalized clipped histogram.

2.5) Equalize the above histogram to obtain the clipped HE mapping for the sub-image [4].

Do the same steps as in AHE for all regions of pixels [3].

III. QUALITY METRICS

All above methods are compared by statistical point of view by using some standard quality measures.

3.1: Michelson contrast

It is measured based on maximum and minimum intensity present in image.

$$Mic = \frac{(Imax - Imin)}{(Imax + Imin)}$$

Where Imax & Imin – maximum and minimum intensities in an image. This value should be 1 which proves that total range of image is maintained constant.

3.2: RMS contrast [8]

It is nothing but standard deviation of an image. It is used to see variation of image from its mean value.

$$\sqrt{\frac{[\sum_{i=0}^{N-1} \sum_{j=0}^{M-1} (I_{ij} - Im)^2]}{M * N}}$$

Where Im - mean of an image

3.3: AMBE [5]

Absolute mean brightness error is the difference between the global mean of input image to the global mean of enhanced image.

$$AMBE = \text{abs}((\text{mean of input image}) - (\text{mean of enhanced image}))$$

3.4: Pixel Distance [1]

$$PixDis = \frac{\sum_{i=0}^{L-2} \sum_{j=i+1}^{L-1} H(i) H(j) (j - i)}{Npix(Npix - 1)} ; \text{for } i, j \in [0, L - 1]$$

Where H(i) - number of pixels in image with grey level i

Npix – total number of pixels

When pixel distance increases, contrast is said to be increased.

IV. RESULTS

4.1: Output Images

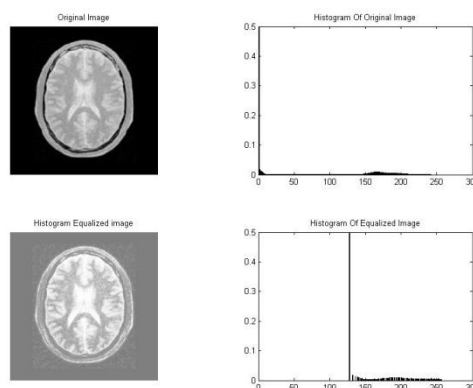


Figure 2: Original & HE images

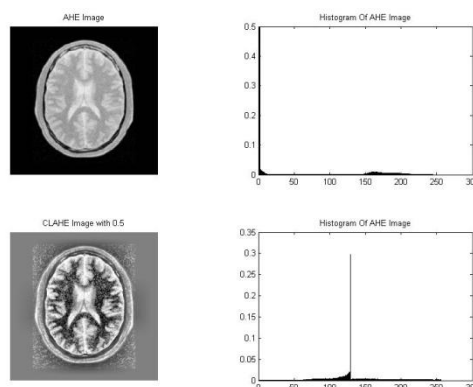


Figure 3: AHE & CLAHE images

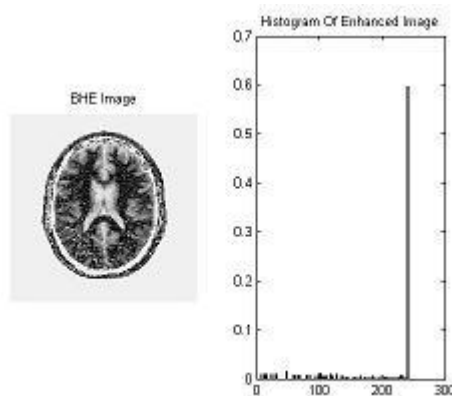


Figure 4: BHE image

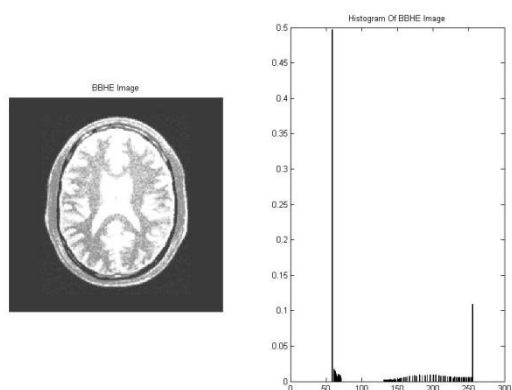


Figure 5: BBHE

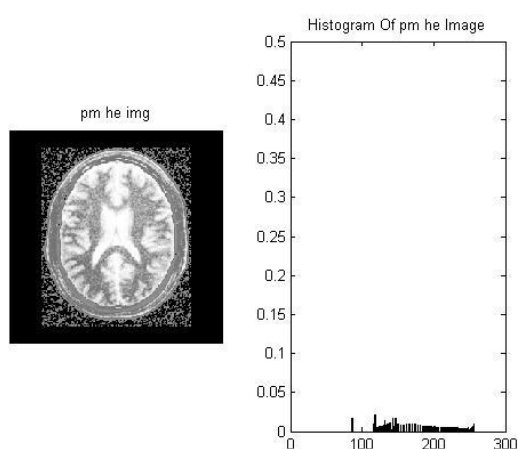


Figure 6: modified BHE

4.2: Quality measures

Table 1: Statistical measures of contrast

	Pixel distance	Michelson contrast	RMS contrast	AMBE
Original	44.076	1	10.091	-
HE	21.546	0.3351	41.567	88.561
BHE	43.894	1	84.613	83.756
Modified BHE	50.276	1	93.144	16.308
BBHE	40.208	1	10.08	48.758
AHE	44.033	1	10.09	0.8689
CLAHE	22.861	1	8.018	61.745

From the above statistics, we can observe that method with low AMBE can preserve average brightness. Here, modified BHE and BBHE are preserving brightness than HE, BHE and CLAHE. The method with less RMS contrast shows that there is no more deviation from mean i.e. mean is preserved for BBHE, AHE & CLAHE. An image with maximum pixel distance is considered to have more contrast. It is observed that modified BHE has more contrast than all others.

V. DISCUSSION

In this paper, we present histogram based approach for contrast enhancement. The good contrast image is useful for detail analysis and diagnosis. This contrast is measured with different objective quality metrics. The MRI data volume is obtained from a simulated brain database [10], which has characteristic of addition of noise in %. All the above methods are applied on different brain MRI images with T1, T2 or PD weighted. CLAHE gives good contrast but has drawback of blocky effect. BBHE is giving better results with respect to histograms also. Modified BHE is having average increase in contrast but again has some blocky effect.

VI. CONCLUSION & FUTURE WORK

This paper presents comparative analysis of different enhancement methods based on histogram processing. It is observed that, for T1 weighted images, modified BHE and CLAHE give good contrast but with some disturbed background. BBHE gives good contrast for the same. For T2 weighted images, CLAHE and BBHE are suitable but BBHE gives uniform histogram and CLAHE gives clipped histogram. For PD weighted images, BBHE or modified BHE are best options. Depending upon original nature of an image, appropriate method should be used for enhancement from mentioned above. The removal of interference and then to use these enhanced images for segmentation or further techniques is future work. Results obtained can also be verified with subjective assessment (MOS ratings).

REFERENCES

- [1] Ali Ziaei, Hojatollah Yeganeh, Karim Faez, Saman Sargolzaei, "A Novel Approach for Contrast Enhancement in Biomedical Images Based on Histogram Equalization", 2008 IEEE International Conference on BioMedical Engineering and Informatics.
- [2] YEONG-TAEGI KIM, "Contrast Enhancement Using Brightness Preserving Bi-Histogram Equalization" IEEE Trans. on Consumer Electronics, Vol.43, No.1, pp.1-8, Feb. 1997.,
- [3]Ramyashree N, Pavithra P, Shruti T V, Dr.Jharna Majumdar, "Enhancement of Aerial and Medical Image using Multi resolution pyramid", Special Issue of IJCCT Vol.1 Issue 2, 3, 4; 2010 for International Conference [ACCTA-2010], 3-5 August 2010.
- [4] A. Boschetti, N. Adami, R. Leonardi M. Okuda, " High Dynamic Range Image Tone Mapping Based On Local Histogram Equalisation", 2010 IEEE.
- [5] S.Palanikumar, M.Sasikumar, J.Rajeesh, " Palmprint Enhancement Using GA-AIVHE Method", ICCCT, IEEE2010.
- [6] Rajesh C. Patil, Dr. A. S. Bhalchandra, " Brain Tumour Extraction from MRI Images Using MATLAB", International Journal of Electronics, Communication & Soft Computing Science and Engineering ISSN: 2277-9477, Volume 2, Issue 1.
- [7] M. Stella Atkins* and Blair T. Mackiewicz, "Fully Automatic Segmentation of the Brain in MRI", IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 17, NO. 1, FEBRUARY 1998.
- [8]Rafael C.Gonzalis,Woods, " Digital image processing", Edition wesley.an imprint of pearson education, 1st edition, 2000 .
- [9] Jorge D. Mendiola-Santibaneza, Ivan R. Terol-Villalobosb, Gilberto Herrera-Ruiza, Antonio Fern´andez-Bouza, "Morphological contrast measure and contrast enhancement: One application to the segmentation of brain MRI", Signal Processing 87 (2007) 2125–2150.
- [10] www.bic.mni.mcgill.ca/brainweb