FUZZY MODEL BASED GRAY LEVEL TRANSFORMATION FOR MRI BRAIN IMAGE ENHANCEMENT

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Abstract: In MRI imaging, the poor contrast image may not provide sufficient data for visual interpretation of affected portions to detect and diagnose various diseases. Therefore, the image enhancement technique is used to improve the medical image visual quality. A simple fuzzified gray level transformation method is proposed for MRI brain image contrast enhancement to improve the contrast without making any loss in image details. The proposed method consists of three stages. First, gray level intensities are transformed to a fuzzy plane whose value range between 0 and 1. Then, the membership values are modified using power law transformation. Finally, modified gray level intensities are obtained via de-fuzzification. By introducing the enhancement parameter, the level of the contrast enhancement can be adjusted based on the input image contrast. The quantitative and subjective enhancement of proposed method is evaluated using two well-known parameters like Entropy or Average Information Contents (AIC) and Feature Similarity Index Matrix (FSIM) for different MRI brain images. Experimental results show that the proposed method can effectively and significantly eliminate washed-out appearance and adverse artifacts induced by several existing methods.

Keywords: Image Enhancement; Histogram Equalization; Entropy; Fuzzy Logic; Gray Level Trans-Formation.

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1 Introduction

Medical Image plays a major role in diagnosing the disease in efficient manner. Magnetic resonance imaging (MRI), Computerized Tomography (CT),) and X-ray imaging are the most common medical imaging technological tool for detecting and diagnosing several diseases. Mostly MRI brain images are poor contrast image and may not provide sufficient data for visual interpretation of affected portions. So, image enhancement technique is needed in medical images to provide a proper diagnosis. The techniques for contrast enhancement include gray-level transformation-based techniques (viz., logarithm transformation, power-law transformation, piecewise-linear transformation) and histogram processing techniques (viz., Histogram Equalization (HE), histogram specification). For gray scale image enhancement, the most popular method is HE, which is based on the assumption that a uniformly distributed gray scale histogram will have the best visual contrast. HE performs its operation by remapping the gray levels of the image based on the probability distribution of the input gray levels. HE tends to introduce some annoying artifacts and unnatural enhancement, including intensity saturation effect. One of the reasons for this problem is because HE normally changes the brightness of the image significantly and thus makes the output image becomes saturated with very bright or dark intensity values. Hence, brightness preserving is an important characteristic needed to be considered in order to enhance the MRI brain image for medical applications.

In order to overcome the limitations of HE and to preserve image brightness, several Brightness

Preserving Histogram equalization techniques have been proposed. At first, Kim proposed Brightness preserving Bi-Histogram Equalization (BBHE)[1,] BBHE divides the input image histogram into two parts based on the mean of the input image and then each part is equalized independently. Consequently, the mean brightness can be preserved because the original mean brightness is retained. Wang et al. proposed Dualistic Sub-Image Histogram Equalization (DSIHE)[2], which is similar to BBHE except that the median of the input image is used for histogram partition instead of mean brightness. Chen and Ramli proposed Minimum Mean Brightness Error Bi-histogram Equalization (MMBEBHE)[3], which is the extension of BBHE method that provides maximal brightness preservation. This algorithm finds the minimum mean brightness error between the original and the enhanced image. Then, it employs the optimal point as the separating point instead of the mean or median of the input image. Though these methods can perform good contrast enhancement[4], they also cause more annoying side effects depending on the variation of gray level distribution in the histogram Ahmed, H.S.S. and M.J. Nordin, Recursive Mean Separate HE (RMSHE)[5]is another improved version of BBHE. This method recursively separates the histogram into multi sub-histograms instead of two sub-histograms as in the BBHE. Initially, two sub-histograms are created based on the mean brightness of the original histogram. Subsequently, the mean brightness from the two sub-histograms obtained earlier is used as the second and third separating points in creating more sub-histograms. In a similar fashion, the algorithm is executed recursively until the desired numbers of sub-histograms are met. Then, the HE approach is applied independently on each of the sub- histogram. The methods discussed above are based on dividing the original histogram into several sub-histograms by using either the median or mean brightness. Although the mean brightness is well preserved by the aforementioned methods, these methods cannot further expand the region of sub-histogram located near to the minimum or maximum value of the dynamic range. However, it is also not free from side effects such as undesirable checkerboard effects on enhanced images and unnatural look.

In order to deal with above problem, Abdullah-Al-Wadud et al. proposed a Dynamic Histogram Equalization (DHE)[6] technique. DHE partitions the original histogram based on local minima. However, DHE does not consider the preserving of brightness. For this purpose, Nicholas et al., proposed Brightness Preserving Dynamic Histogram Equalization (BPDHE)[7]. This method partitions the image histogram based on the local maxima of the smoothed histogram. It then assigns a new dynamic range to each partition. Finally, the output intensity is normalized to make the mean intensity of the resulting image equal to the input one. Although the BPDHE performs well in mean brightness preserving, the ratio for brightness normalization plays an important role. A small ratio value leads to insignificant contrast enhancement. For large ratio (i.e., ratio value more than 1), the final intensity value may exceed the maximum intensity value of the output dynamic range. The exceed pixels will be quantized to the maximum intensity value of gray levels and produce intensity saturation problem (in MATLAB environment). Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE)[8]has been proposed by Debdoot Sheet et al. which is an enhanced version of BPDHE. The BPDFHE technique manipulates the image histogram in such a way that no remapping of the histogram peaks takes place, while the only redistribution of the gray-level values in the valley portions between two consecutive peaks takes place. The results using BPDFHE method show well enhanced contrast and little artifacts.

To overcome the abovementioned drawbacks, many researchers introduced the fuzzy set theory for image enhancement. This theory is popular among the researchers because it is a suitable tool for dealing with the uncertainties and it provides a solution to the problem of precision between classical mathematics and the inherent precision of the real world. The imprecision possessed by the acquired image can be qualitatively perceived by human reasoning. However, no specific quantification can describe imprecision. Thus, a machine may not understand the imprecision. Realizing this limitation, the fuzzy logic tools become a popular choice because it empowers a machine to mimic human reasoning that suitable for image enhancement. The same fuzzy logic tool is applied to medical images results in contrast enhancement which yields in effective disease diagnosis. At first, using fuzzy logic contrast enhancement of medical data sets using fuzzy set[9] is proposed by Tamalika Chaira. Based on the average of an image a new membership modification factor is found. The image with new membership function results in an enhanced image. V Magudeeswaran et al., proposed bi-level fuzzy histogram equalization(BPBFHE)[10] method for contrast enhancement of brain MRI image. In this method fuzzy logic[11, 13] is applied to the input image and that fuzzified image is subdivided into two based on its mean and then it is equalized. Through this original brightens of brain MRI image is preserved.

Even though existing methods suffer from unwanted over-enhancement and noise amplification. So fuzzy power law algorithm is proposed for brain MRI images. In the proposed method, first, gray level intensities are transformed to a fuzzy plane whose value range between 0 and 1. Then, the membership values are modified using power law transformation. Finally, modified gray level intensities obtained via de-fuzzification.

The rest of this study is organized as follow. In Sect. 2, the Conventional Histogram Equalization is explained in detail. The proposed algorithm for fuzzification and enhancement are presented in Sect. 3. Simulation of the test images and the qualitative and quantitative comparison of the results are discussed in Sect. 5 and 6. Finally, Sect. 7 concludes this study.

2 Histogram Equalization

The histogram is defined as the statistical probability distribution of each gray level in a digital image. Histogram Equalization (HE) is a very popular technique for contrast enhancement of images. The contrast of images is determined by its dynamic range, which is defined as the ratio between the brightest and the darkest pixel intensities. The histogram provides information for the contrast and overall intensity distribution of an image.

Let F be the input image composed of L discrete gray levels denoted as $\{F_0, F_1,\ldots F_{L-1}\}$. For a given image F, the probability density function $P(F_k)$ is defined as:

$$P(F_k) = \frac{n^k}{n} \tag{1}$$

for k = 0, 1, 2, …, L-1, where n^k represents the number of times that the gray level F_k appears in the input image F and n is the total number samples in the input image. Note that P (F_k) is associated with a histogram of the input image which represents the number of pixels that have a specific intensity F_k. In fact, a plot of F_k Vs n^k is called as a histogram of input image F. The respective cumulative density function is then defined as:

$$C(F_k) = \sum_{j=0}^{k} P(F_j) \tag{2}$$

For k = 0, 1, 2,…, L-1. Note that C (F_{L-1}) =1 by definition. Histogram equalization is a method that maps the input image into entire dynamic range, $(F_0 - F_{L-1})$, by using the cumulative distribution function as an action f(x) based on cumulative density function as:

$$f(x) = \{F_0 + (F_{L-1} - F_0)C(F_k)\} \tag{3}$$

Then, the enhanced image of HE Y=Y (i, j) can be expressed as:

$$Y = f(x) = \{f(F(i,j)) \forall F(i,j) \in F\} \tag{4}$$

However, HE produces an undesirable checkerboard effects on enhanced brain images. Another problem with this method is that it also enhances the noises in the input image along with the image features[14-15].

3 Proposed Work

Fuzzy image enhancement is done by mapping image gray level intensities into a fuzzy plane using membership function and then modifies those member functions for contrast enhancement and map the fuzzy plane back to image gray level intensities. The aim of the proposed method is to generate an image of higher contrast than the original image by giving the larger weight to the gray levels that are closer to the mean gray level of the image than to those that are farther from the mean.

The proposed fuzzy enhancement involves three stages namely image fuzzification, modification of membership values for image enhancement and image defuzzification. In image fuzzification, gray level intensities are transformed to a fuzzy plane whose value range between 0 and 1. Consider an image f of size M*N and intensity level in the range (0, L−1) as a set of fuzzy singletons in the fuzzy set notation, each with a membership function denoting the degree of having some gray level. The fuzzy matrix F corresponding to this image can be expressed as:

$$F= \cup_{x=1}^{M} \cup_{y=1}^{N} \frac{\mu_{xy}}{f_{xy}} \qquad 0 \leq \mu_{xy} \leq 1 \qquad (5)$$

where, f_{xy} is the intensity of $(m, n)^{th}$ pixel and μ_{xy} its membership value. The original image f in the spatial do-main will be converted to a fuzzy domain using a specific membership function according to its region (i.e., dark or bright regions).

To enhance the image, we concentrate on contrast enhancement. This is achieved by making dark pixel darker and bright pixel brighter. The pixel having middle-intensity value is not changed much. Hence, Contrast intensification is applied to the reduces amount of fuzziness of F by increasing the values of above 0.5 and decreasing those below it. This contrast intensification operator on the fuzzy set F generates another fuzzy set, the membership function of which can be expressed as follows:

$$f_{xy}=\begin{Bmatrix} 2 \times \mu_{xy}^2 & if\ \mu_{xy} < 0.5 \\ 1-2\times\left(1-\mu_{xy}\right)^2 & if\ 0.5 < \mu_{xy} \leq 1 \end{Bmatrix} \qquad (6)$$

The membership function is then modified according to its respective region to enhance the image once the image is converted into the fuzzy domain. The power law transformation is used for enhancing the dark (underexposed) and bright (overexposed) regions. The power-law transformation is usually defined as:

$$S = (Cr_{xy})^{\gamma} \qquad (7)$$

where S is the gray levels of the pixels in the output image and C is a constant. The modified membership functions are defuzzified using their respective inverse membership functions:

$$\begin{aligned} G(x,y) &= T^{-1}\left(S(x,y)\right) \\ &= \cup_{x=1}^{M} \cup_{y=1}^{N} S(x,y) * (L-1) \end{aligned} \qquad (8)$$

where, G(x, y) denotes the gray level of the $(x, y)^{th}$ pixel in the enhanced image, T^{-1} denotes the inverse transformation of T. It means that the membership values are re-transformed into the gray-level plane. This method produces better perceptible results as compared to other conventional methods.

4 Image Quality Assessment

Image Quality Assessment (IQA) aims to use computational models to measure the image quality consistently with subjective evaluations. IQA indices used in our evaluation include the Feature Similarity (FSIM) index and Average Information Contents (AIC) for measuring image quality[12].

The computation of FSIM index consists of two stages. In the first stage, the local similarity map is computed and then in the second stage, we pool the similarity map into a single similarity score. We separate the feature similarity measurement between $f_1(x)$ and $f_2(x)$ into two components, each for Phase Congruency (PC) or Gradient Magnitude (GM). First, the similarity measure for $P_{C1}(x)$ and $P_{C2}(x)$ is defined as:

$$S_{PC}(x) = \frac{(2PC_1(x).PC_2(x)+T_1)}{(PC_1^2(x).PC_2^2(x)+T_1)} \qquad (9)$$

where T_1 is a positive constant to increase the stability of S_{PC}. Similarly, the GM values $G_1(x)$ and $G_2(x)$ are com-pared and the similarity measure is defined as

$$S_C(x) = \frac{(2G_1(x).PG_2(x)+T_2)}{(PG_1^2(x).PG_2^2(x)+T_2)} \quad (10)$$

where T_2 is a positive constant depending on the dynamic range of GM values. In our experiments, both T_1 and T_2 will be fixed to all databases so that the proposed FSIM can be conveniently used. Then, $S_{PC}(x)$ and $S_G(x)$ are combined to get the similarity SL(x) of $f_1(x)$ and $f_2(x)$. We define $S_L(x)$ as $S_L(x) = S_{PC}(x)\ S_G(x)$. Therefore, we use $PC_m(x) = \max(P_{C1}(x), P_{C2}(x))$ to weight the importance of $S_L(x)$ in the overall similarity between f_1 and f_2 and accordingly the FSIM index between f_1 and f_2 is defined as:

$$\text{FSIM}(x)= \frac{\sum_{x\in\Omega} S_L(x) PC_m(x)}{\sum_{x\in\Omega} PC_m(x)} \quad (11)$$

where Ω means the whole image spatial domain. Moreover, the AIC is used to measure the content of an image, where a higher value indicates an image with richer details. Greater the AIC is the better. A higher value of the AIC indicates the more information is brought out from the medical images. NIQE is used for measuring image quality. Smaller the NIQE is the better. Smaller NIQE indicates better image quality. The average information contents or entropy is defined as:

$$AIC = -\sum_{k=0}^{L-1} p(k)\ log\ p(k) \quad (12)$$

where p(k) is the probability density function of the kth gray level.

5 Results and Discussions

In this section, comparison among the proposed method and several other conventional methods such HE, BBHE, MMBEBHE and BPDFHE are presented. A subjective assessment to compare the visual quality of the MRI brain images is carried out. Average Information Content (AIC) or Entropy, Structural Similarity Index Matrix (SSIM), the feature similarity (FSIM) index and Natural Image Quality Evaluator (NIQE) index are used to assess the effectiveness of the proposed method.

Figs. 1 and 2 show the resulting MRI brain image obtained by the various existing methods and the proposed method. Figs. 1 and 2 b shows that HE provides a significant improvement in image contrast. However, it also amplifies the noise level of the MRI brain image along with some artifacts and undesirable side effects such as washed out appearance. Figs.1 and 2 c show that the BBHE method produces the unnatural look and insignificant enhancement to the resultant image. However, it also has an unnatural look because of over-enhancement in brightness.

The results of MMBEBHE and BPDFHE (Figs. 1 and 2 d & e) show good contrast enhancement, they also cause more annoying side effects depending on the variation of gray level distribution in the histogram. Thus, the enhancement results of MMBEBHE and BPDFHE are visually unpleasing. Further, the qualities of the test MRI brain images which are enhanced using the above-mentioned techniques are measured in terms of Entropy, FSIM is given in Table 1 and 2 respectively.

The proposed method was tested with several MRI brain images and has been compared with other conventional methods HE, BBHE, MMBEBHE and BPDFHE. The results of HE, BBHE, MMBEBHE and BPDFHE show that they do not prevent the washed-out appearance in the overall image due to a significant change in brightness. The results show that the proposed method preserves the naturalness of image and also prevent the side effect due to the significant change in brightness effectively.

According to Table 1, the proposed method produces the highest AIC, thus becomes the best method to bring out the details of the images. In addition, the AIC results show that the proposed method improves the contrast of the MRI brain input images in a better way, which is numerically indicated by the greater AIC values as compared to the other conventional methods. From the analysis of FSIM values furnished in Table 2, it is found that proposed method has produced values that are closer to 1, which signifies the similarity between the original and the enhanced images. Hence, proposed method produces enhanced images with natural looking. Based on qualitative and quantitative analyses, the proposed method has been found effective in enhancing contrasts of MRI brain images in comparison to a few existing methods. The performance of the proposed method has been compared with five state-of-the-art methods, both quantitatively and visually. Experimental results show that the proposed method not only outperforms in contrast enhancement but also provides good visual representation in visual comparison.

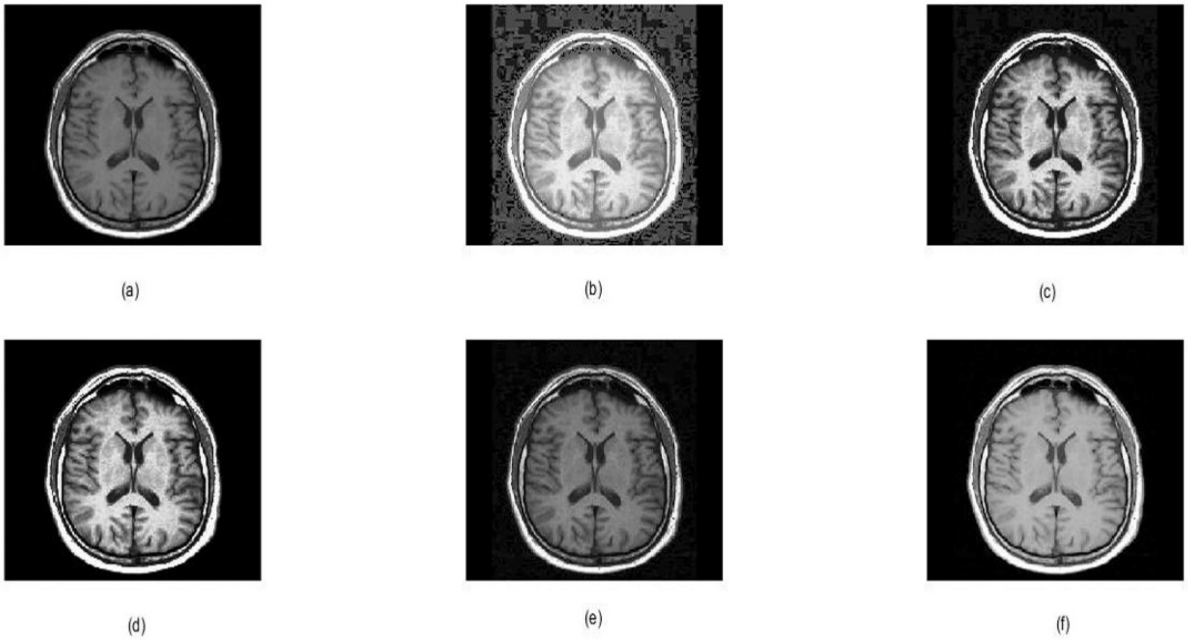

Fig.1 Simulation results of the brain image1. (a). Original image; (b). HE-ed image; (c). BBHE-ed image; (d). MMBEBHE-ed image; (e). BPDFHE-ed image; f. Proposed image.

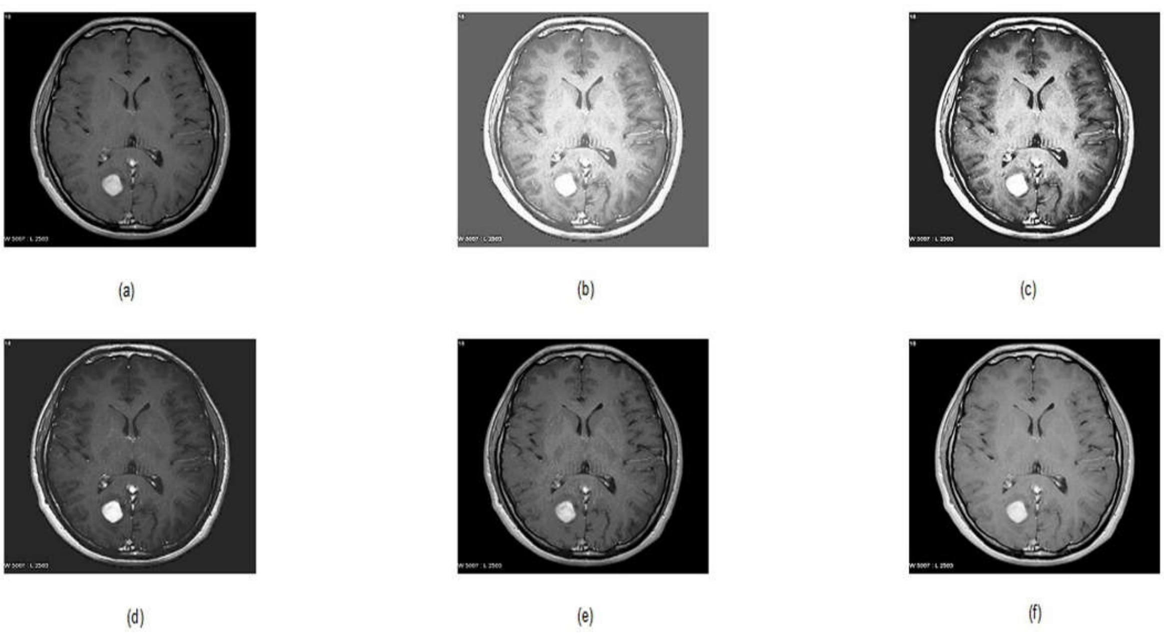

Fig.2 Simulation results of the brain image2. (a). Original image; (b). HE-ed image; (c). BBHE-ed image; (d). MMBEBHE-ed image; (e). BPDFHE-ed image; f. Proposed image.

Table 1: Comparison of AIC values

Image ID	HE	BBHE	MMBEBHE	BPDFHE	Proposed Method
Image 1	5.25	5.33	5.38	5.43	5.61
Image 2	4.55	5.23	5.55	5.75	5.76
Image 3	5.41	5.52	5.45	6.23	6.22
Image 4	4.26	5.87	5.92	6.38	6.40
Image 5	5.12	6.01	5.81	5.92	5.92
Image 6	4.89	5.32	5.69	5.89	5.91
Image 7	5.81	6.23	6.25	7.02	7.10
Image 8	5.78	6.13	6.38	6.77	6.81
Image 9	4.03	5.21	5.14	5.29	5.33
Image 10	5.23	5.74	5.87	6.23	6.23
Average	5.03	5.65	5.74	6.09	6.12

Table 2: Comparison of FSIM values

Image ID	HE	BBHE	MMBEBHE	BPDFHE	Proposed Method
mage 1	0.78	0.85	0.84	0.78	0.81
Image 2	0.73	0.84	0.84	0.80	0.85
Image 3	0.74	0.83	0.87	0.91	0.95
Image 4	0.93	0.89	0.88	0.90	0.93
Image 5	0.77	0.83	0.86	0.89	0.90
Image 6	0.67	0.87	0.88	0.93	0.94
Image 7	0.81	0.93	0.86	0.94	0.96
Image 8	0.72	0.83	0.87	0.86	0.87
Image 9	0.65	0.74	0.91	0.88	0.88
Image 10	0.87	0.88	0.87	0.90	0.92
Average	0.76	0.84	0.86	0.88	0.91

6 Conclusion

In this study, a simple fuzzy logic based gray level transformation is presented for MRI brain image contrast enhancement. The significant change in brightness caused by conventional contrast enhancement methods may bring undesired artifacts and unnatural look image. Furthermore, the proposed method can preserve naturalness of an image and prevent significant change in brightness by using the adaptive scale factor. The experimental results showed that proposed method prevented excessive enhancement in contrast and preserved naturalness of an MRI brain image than the conventional methods.

References

1. Kim, Y.T. Contrast enhancement using brightness preserving bi-histogram equalization. *IEEE Trans. Consumer Electronics*, 1997;43: 1-8.
2. Yu Wang, Qian Chen, Nanjing, P.R. China. Image enhancement based on equal area dualistic. *IEEE Transactions on Consumer Electronics*,1999;45(1):68-75.
3. Chen, S.D. and A.R. Ramli. Minimum mean brightness error bi-histogram equalization in contrast enhancement. *IEEE Tran. Consumer Electronics*, 2003; 49: 1310-1319.
4. Ahmed, H.S.S. and M.J. Nordin. Improving diagnostic viewing of medical images using enhancement algorithms. *J. Comput. Sci*. 2011; 7: 1831-1838.

5. Kim, M. and M.G. Chung. Recursively Separated and Weighted Histogram Equalization for Brightness Preservation and Contrast Enhancement. *IEEE Transactions on Consumer Electronics*, 2008; 54(3):1389-1397.
6. Abdullah-Al-Wadud, M., H. Kabir, M.A.A. Dewan and O. Chae. A dynamic histogram equalization for image contrast enhancement. *IEEE Trans. Consumer Electronics*.2007; 53: 593-600.
7. Nicholas, S., P. Kong and H. Ibrahim. Color image enhancement using brightness preserving dynamic histogram equalization. *IEEE Trans. Consumer Electronics*.2008;54(4):1962-1967.
8. Debdoot Sheet, HrushikeshGarud, Amit Suveer, Manjunatha Mahadevappa, Jyotir Chatterjee. Brightness preserving dynamic fuzzy histogram equalization. *IEEE Trans.Consumer Electronics*.2010;56(4):2475-2480.
9. Tamalika Chaira. Contrast enhancement of medical images using type II fuzzy set. *National Conference on Communications (NCC)*.2013;10:1-5.
10. V Magudeeswaran, CG Ravichandran, P Thirumurugan. Brightness preserving bi-level fuzzy histogram equalization for MRI brain image contrast enhancement. *International Journal of Imaging Systems and Technology*.2017;27(2):153-161.
11. V Magudeeswaran, CG Ravichandran. Fuzzy logic-based histogram equalization for image contrast enhancement. *Mathematical Problems in Engineering*.2013;1-10.
12. Randeep Kaur, Sandeep Kaur. Comparison of contrast enhancement techniques for medical image. *Emerging Devices and Smart Systems (ICEDSS) IEEE*. 13 October 2016.
13. Taranbir Kaur, Ravneet Kaur Sidhu. Performance Evaluation of Fuzzy and Histogram Based Color Image Enhancement. *Procedia Computer Science*.2015;58:470-477.
14. Chen Hee Ooi, Nor Ashidi Mat Isa. Quadrants dynamic histogram equalization for contrast enhancement. *IEEE Transactions on Consumer Electronics*. 2010;56(4): 2552 – 2559.
15. M. Sundaram, K. Ramar, N. Arumugam, G. Prabin. Histogram Modified Local Contrast Enhancement for mammogram images. *Applied Soft Computing*.2011;11:5809-5816.