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A NOVEL EXPERIMENTAL EVALUATION FOR THE 'DEVELOPMENT OF A NOVEL STANDARD NOTION', IMAGE QUALITY ASSESSMENT (IQA) MEASURES, COMPUTATIONAL TIME FOR IMAGE CONTRAST ENHANCEMENT

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ABSTRACT

In this research we did quantification of contrast level for various general and biomedical images. Here we considered two novel techniques under evaluation first one is Histogram Flatness Measure (HFM) and second one is Histogram Spread (HS). In case of HFM the values of the measure are found to be inconsistent in the sense that even for low contrast images also the value of HFM are higher than original images being inconsistent to identify whether it is high contrast or low contrast image with respect to original image. When it comes to HS the values of the measure are coming as for high contrast images high values of HS and low contrast images low values of HS with respected to the value of Original Image. Here we observed the values in terms of taking the images of high contrast at certain level to fully high contrast (histogram equalized images). For all the high contrast images HS found to be high values and low contrast images HS found to be low values and being highly consistent and specifically useful than HFM. The standardization of HS can be useful in database management, visualization, image classification. As par the images we put into application for the evaluation of Novel metric 'HS', then we may standardize the notion "High contrast high value and low contrast low value". Then we did want to analyze the images of high contrast which follow the notion along with images of histogram equalized high contrast images for every image under consideration, in terms of image contrast enhancement Image Quality Assessment (IQA) measures, and we would like to find out the image whether if it is higher level of high contrast or lower level of high contrast with respected to the fully high contrast (histogram equalized) image, so that we can have an idea of the given partially high contrast (towards histogram equalization) image that how much near it is to Fully high contrast image. One advantage of this observation is that, if the image is high contrast and if it is far from fully high contrast image, then we can become cautious especially In the case of Biomedical Images, Cosmological images that the images have to be carefully preserved. Here we have found the Computational time in milliseconds for each IQA measure for all the images so that we can have an idea of which measure we can choose for any hardware design of the performance measure by using tradeoffs basing on the required application of interest of any high speed Digital Image Processor Hardware Implementation for any Real time Medical Device. The image quality measures we considered are Peak Signal–to-Noise-Ratio (PSNR), Mean Absolute Error (MAE), Absolute Mean Brightness Error (AMBE), Signal to Noise Ratio (SNR), Contrast to Noise Ratio (CNR), Universal Quality Index (UQI), Noise Quality Measure (NQM), Structural SIMilarity (SSIM), Mean SSIM(MSSIM), Information Fidelity Criterion(IFC), Visual Information Fidelity (VIF), Visual Information Fidelity in Pixel Domain (VIFP), Visual Signal-to-Noise Ratio (VSNR), Wavelets Based SNR (WSNR), Feature similarity Metric (FSIM), Riesz Transform FSIM (RFSIM). One more observation we made is that partially high contrast images are having low computational time of performance metrics when compared to fully high contrast (histogram equalized) images. So in some applications, where no need of fully high contrast images, we can utilize these reasonably high contrast images instead of fully high contrast images for reducing the computational time and also it is highly useful in the case of Digital Image Processing hardware design for saving time and to get a high speed processor, which is highly useful observation. All the research is done in MATLAB
8.3 R2014a programming.

KEYWORDS: Image contrast enhancement, histogram equalization, HS, HFM, Image Quality Assessment (IQA), MAE, PSNR, AMBR, RFSIM, WSNR, MATLAB.

INTRODUCTION

Image contrast enhancement techniques play an important role to improve the visual appearance of a digital image so that extracting image details becomes easy. These techniques have varied applications in medical image processing like detection of cancers, tumors etc., seismic exploration, video processing, camera and surveillance. Image enhancement process consist of a collection of techniques that seek to improve the visual appearance of an image or to convert the image to a form better suited for analysis by a human or machine. Image enhancement means as the improvement of an image appearance by increasing dominance of some features or by decreasing ambiguity between different regions of the image. The objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application. Image enhancement is one of the most interesting and visually appealing areas of image processing. Image enhancement is broadly divided into two categories: spatial domain methods and frequency domain methods. Image enhancement, which is one of the significant techniques in digital image processing, plays important roles in many fields, such as medical image analysis, remote sensing, high definition television (HDTV), hyper spectral image processing, industrial X-ray image processing, microscopic imaging etc [1,14]. Image enhancement is a processing on image in order to make it more appropriate for certain applications. It is mainly utilized to improve the visual effects and the clarity of the image, or to make the original image more conducive for computer to process. Generally, an image may have poor dynamic range or distortion due to the poor quality of the imaging devices or the adverse external conditions at the time of acquisition. The contrast enhancement is one of the commonly

used image enhancement methods. Many methods for image contrast enhancement have been proposed which can be broadly categorized into two methods: direct methods and indirect methods [1,14]. Among the indirect methods, the histogram modification techniques have been widely utilized because of its simplicity and explicitness [13]. Contrast enhancement changing the pixels intensity of the input image to utilize maximum possible bins [7]. Contrast enhancement is based on five techniques such as local, global, partial, bright and dark contrast. Main problem is to identity whether the contrast enhancement is needed for the images or not. Contrast enhancement of a good image many lead to an overexposed or saturated image [8, 9]. So we need a metric which can effectively quantify the contrast and thereby discriminate the good and poor contrast images [12]. So we have considered two proposed methods under evaluation; to identify which one is best for developing a sure approach and to develop a notion of "low contrast low value and high contrast high value". The approaches we have considered are histogram flatness measure (HFM) and histogram spread (HS). We did extensive application of general and biomedical images and HS found to be best and sure approach as a performance metric which follows the notion "low contrast low value; high contrast high value". Then we consider most important Image Quality Assessment (IQA) Measures for observing the quality of each image, and we also observed the computational time for each method. We did some analysis on these measures and we made some highly useful conclusions on hardware implementations of Digital Image Processors.

This research is organized in this way: Section II explains about mathematical analysis of HFM, HS metrics. Section III analyzes the mathematics behind the Image Quality Assessment Measures. Section IV provides the MATLAB simulation results for HFM, HS & for all IQA measures, Computational time; and critical analysis on the observed results is made. We made advanced conclusions and provided in section V.

HISTOGRAM FLATNESS MEASURE (HFM) and HISTOGRAM SPREAD (HS)

Image quality assessment in digital domain is critical [2,3] in all applications of image processing. Image enhancement provides to enhance the apparent visual quality of an image or emphasize certain features based on the knowledge of source of degradation [4,5]. Image contrast is an important feature of image enhancement. Here in this research we have taken into consideration of two novel methods under evaluation and applied on some images. Those two novel techniques under evaluation are [9,10]

1. Histogram Flatness Measure (HFM)
2. Histogram Spread (HS)

These two we have utilized for image contrast enhancement performance analysis to have a quantifying measure for the notion **"low contrast low value; high contrast high value".** These two techniques HFM and HS are based on the statistical parameters of image histogram like geometric mean, quartile distance and range.

Histogram Flatness Measure (HFM):
It follows in parallel to Spectral Flatness Measure. For our images of interest digital images, we define here HFM as [9,10]

HFM = (geometric mean of histogram count) / (arithmetic mean of histogram count)

$$HFM = [(\prod_{i=1}^{n} x_i)^{1/n}]/[1/n \sum_{i=1}^{n} x_i] \quad (1)$$

x_i – Histogram count for the i^{th} histogram bin n

– Total number of histogram bins

As per the formula HFM € [0, 1]; and also it is clear that low contrast images have low value of HFM with respect to high contrast images.

Histogram Spread (HS):
HS = (Quartile Distance of Histogram)/(Possible Range of Pixel Values)

= [(3rd Quartile – 1st Quartile) of Histogram] / [(maximum – minimum) of the pixel value range]

3rd quartile means that histogram bins at which cumulative histogram has 75% of the maximum value

1st quartile means that histogram bins at which cumulative histogram have 25% of the maximum value
Range is the difference between the possible maximum and minimum intensities of the image. HS [9,10] ranges from (0, 1]; for unimodal to multimodal histograms. It is clear that low contrast images have low value of HS with respect to high contrast images.

IMAGE QUALITY ASSESSMENT MEASURES
Here in this research we considered various image quality measures. We put into application of these measures for all the images we put into application of HS and HFM. The measures are [1,6,11]

Peak Signal–to-Noise-Ratio (PSNR), Mean Absolute Error (MAE), Absolute Mean Brightness Error (AMBE), Signal to Noise Ratio (SNR), Contrast to Noise Ratio (CNR), Universal Quality Index (UQI), Noise Quality Measure (NQM), Structural SIMilarity (SSIM), Mean SSIM(MSSIM), Information Fidelity Criterion(IFC), Visual Information Fidelity (VIF), Visual Information Fidelity in Pixel Domain (VIFP), Visual Signal-to-Noise Ratio (VSNR), Wavelets Based SNR (WSNR), Feature similarity Metric (FSIM), Riesz Transform FSIM (RFSIM).

As all of these measures are highly standard, well known and some may be complicated to utilize, and all these are frequently used Image Quality Assessment Measures, here we are providing some descriptions along with formulations for some of these measures.

Peak-Signal-to-Noise-Ratio (PSNR):
If there is an input image X (i, j), and a processed image Y (i, j), M×N image size Then calculate first Mean Square Error (MSE),

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} |X(i,j)-Y(i,j)|^2}{M \times N} \quad (2)$$

Then PSNR is

$$PSNR = 10 \log_{10} \frac{(L-1)^2}{MSE} \quad (3)$$

Absolute Mean Brightness Error (AMBE):

$$AMBE(X,Y) = |X_M - Y_M| \quad (4)$$

X_M – mean of input image X = {x(i,j)}
Y_M – mean of output image Y = {y(i,j)}
Low value of AMBE represents better brightness preservation.

Structured SIMilarity index (SSIM):

It is also useful to measure similarity between two images. It is a full reference metric for the measuring of image quality based on an initial image as reference. If μ_x is mean of image x, μ_y is mean of y; σ_x, σ_y, are standard deviations of images x, y; then σ_{xy} square root of covariance of image x and y and C_1, C_2 are constants.

$$SSI(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (5)$$

Mean Absolute Error:

$$MAE(r,e) = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}|n(i,j)| \quad (6)$$

M×N is size of the image; r and e are reference image and contrast image respectively, n(i, j) = r(i, j) – e(i, j). Low value represents better quality of image.

Contrast-to-Noise Ratio

$$CNR(r,e) = \frac{\mu_r - \mu_n}{\sigma_n} \quad (7)$$

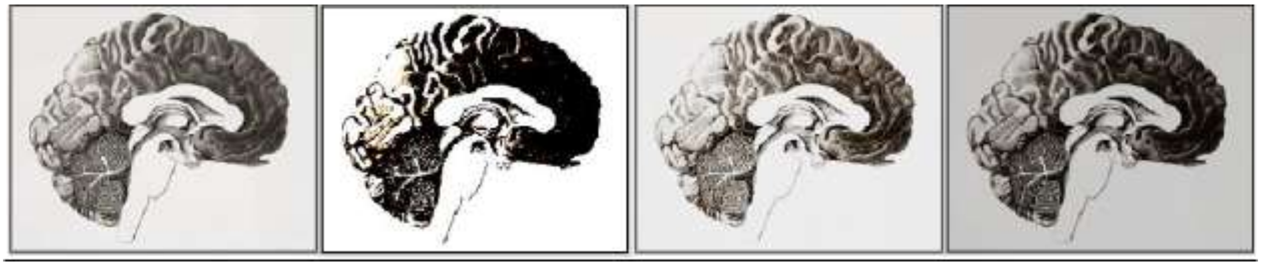
$$\mu_r = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} r(i,j) \quad (8)$$

$$\mu_n = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(n(i,j)) \quad (9)$$

$$\sigma_n^2 = \frac{1}{MN-1}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(n(i,j) - \mu_n)^2 \quad (10)$$

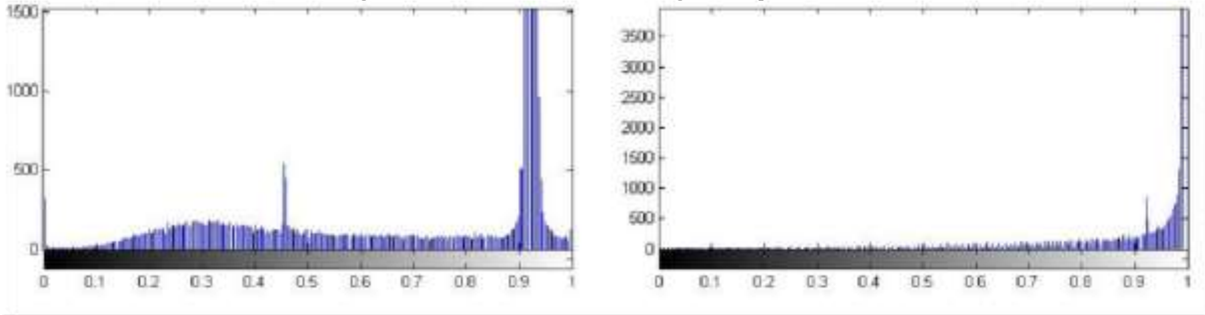
M×N is size of the image; r and e are reference image and contrast image respectively, n(i, j) = r(i, j) – e(i, j).

SIMULATION RESULTS ANALYSIS CALCULATION OF 'HFM & HS'

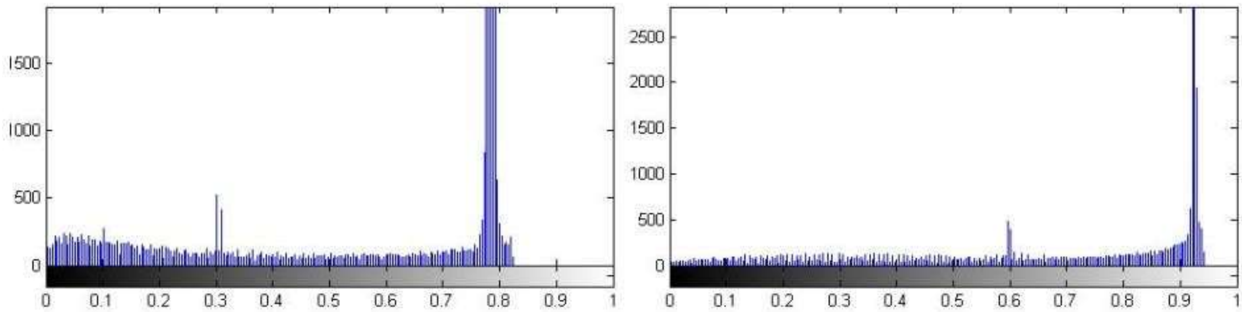


(a) (b) (c) (d)

Figure 1 Brain Image (a) Original Image (b) Low Contrast Dark Image (c) Low Contrast Bright Image (d) High Contrast, towards to histogram equalization



(a) **(b)**



(a) **(b)**

Figure 2 Brain Image Histograms (a) Original Image (b) Low Contrast Dark Image (c) Low Contrast Bright Image (d)High Contrast, towards histogram equalization

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

Figure 3 Retinal Image (a) Original Image (b) Low Contrast Dark Image (c) Low Contrast Bright Image (d) High Contrast, towards histogram equalization

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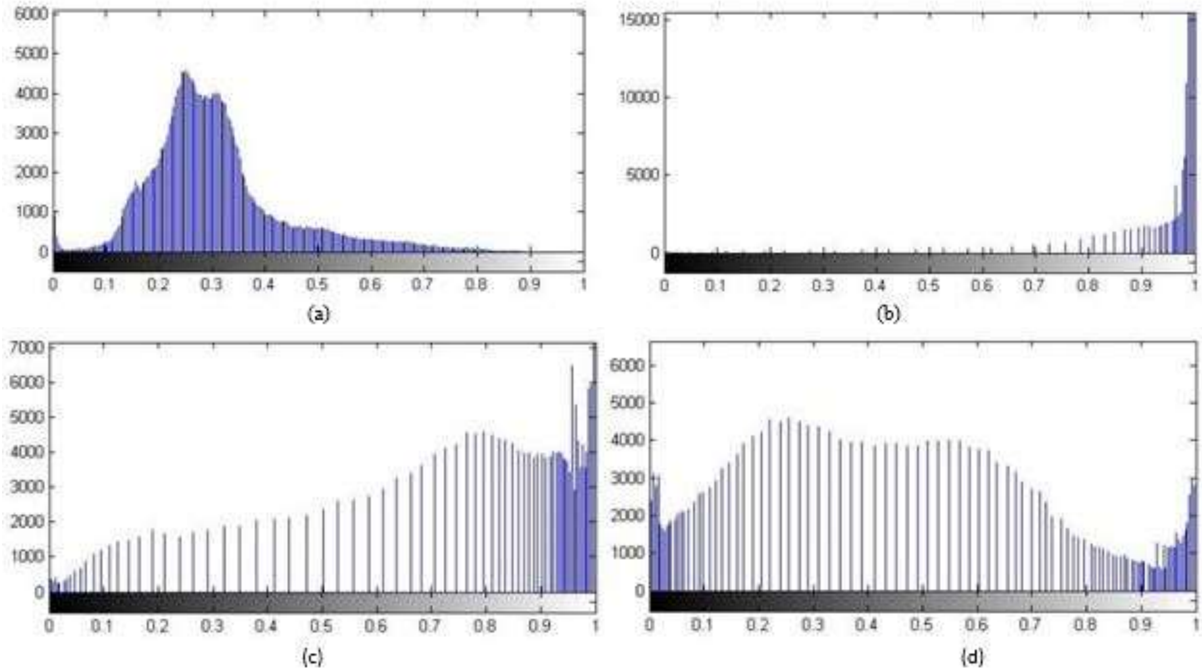


Figure 4 Retinal Image Histograms (a) Original Image (b) Low Contrast Dark Image (c) Low Contrast Bright Image(d) High Contrast, towards histogram equalization

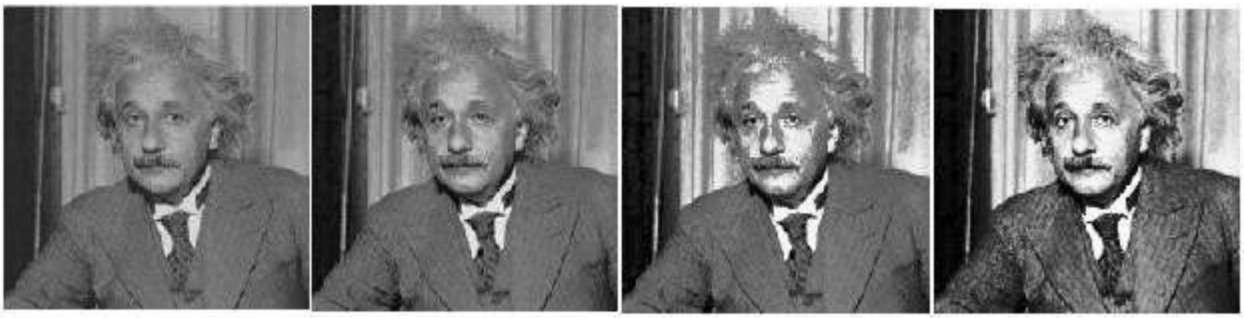


Figure 5 Einstein Image 1 (a) Original Image (b) Low Contrast Dark Image (c) Low Contrast Bright Image (d) High Contrast, towards histogram equalization

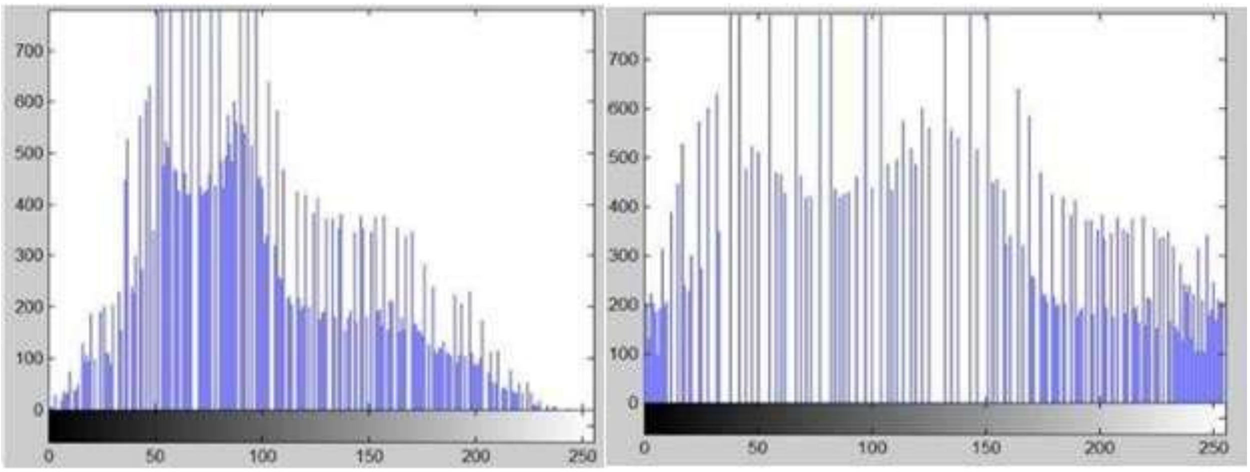
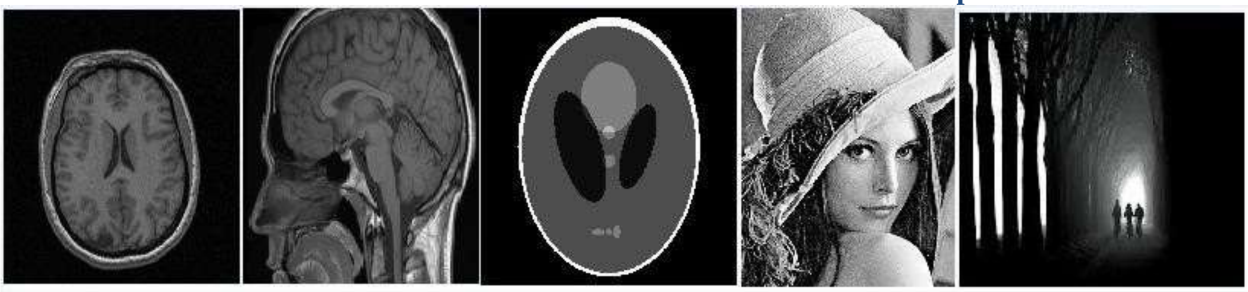


Figure 6 Einstein Image 1 Histograms (a) Original Image Histogram (b) High Contrast, towards histogram equalization



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

(f) (g) (h) (i) (j)

Figure 7 Various Images considered for evaluation of HS and HFM; and also for Performance measures (a) brain image 1 (b) brain image 2 (c) Brain Shepp-Logan phantom image (d) Lena Image (e) cycle tree cave image (f) Flowers diagram image (g) building street image (h)Taj mahal image (i) tower of Pisa (j) Einstein image 2

Serial Number	Image Name	Original	Low Contrast (dark)	Low contrast (bright)	High contrast (histogram towards equalization)
1	Brain Image	0.5678	0.5778	0.6789	0.7910
2	Retinal Image	0.6789	0.3456	0.6799	0.7890
3	Brain Image 1	0.7896	0.2341	0.7654	0.8345
4	Brain Image 2	0.5432	0.4567	0.4967	0.5789
5	Brain Phantom	0.7865	0.4356	0.7989	0.8787
6	Lena	0.6754	0.3432	0.5672	0.6980
7	Cycle tree cave	0.5643	0.1234	0.4512	0.6732
8	Flowers Diagram	0.1456	0.0987	0.2114	0.2301
9	Building Street	0.2387	0.1567	0.3001	0.2456
10	Tajmahal	0.3421	0.3321	0.3412	0.4210
11	Tower of Pisa	0.4532	0.2314	0.3256	0.5041
12	Einstein 1	0.5123	0.2001	0.2209	0.6543
13	Einstein 2	0.5901	0.2309	0.3392	0.6415

Table 1 Histogram Flatness Measure (HFM) For Test Images for Different Contrast Condition

Serial Number	Image Name	Original	Low Contrast (dark)	Low contrast (bright)	High contrast (histogram towards equalization)
1	Brain Image	0.3421	0.1245	0.2345	0.4456
2	Retinal Image	0.4321	0.2345	0.2876	0.4897
3	Brain Image 1	0.4456	0.3346	0.3567	0.4567
4	Brain Image 2	0.3324	0.2134	0.2234	0.4502
5	Brain Phantom	0.3432	0.2363	0.2678	0.4034
6	Lena	0.4834	0.2345	0.3980	0.4987
7	Cycle tree cave	0.4567	0.2387	0.2534	0.4908
8	Flowers Diagram	0.3879	0.2301	0.3210	0.4321
9	Building Street	0.4678	0.3246	0.3345	0.5467
10	Tajmahal	0.4578	0.4046	0.4123	0.4992
11	Tower of Pisa	0.4302	0.3240	0.3999	0.4560
12	Einstein 1	0.5789	0.3987	0.4789	0.6754
13	Einstein 2	0.4589	0.3998	0.4031	0.4987

Table 2 Histogram Spread (HS) for test images for different contrast condition

CALCULATION OF IMAGE QUALITY ASSESSMENT (IQA) MEASURES

Image contrast enhancement performance metric	Low contrast(dark) w.r.t. original image	Low contrast (bright) w.r.t. original	High Contrast (histogram towards equalization)	Computational time for High contrast image (In ms)	Fully High contrast (histogram equalized)	Computational time for Fully High contrast image (In ms)
PSNR(dB)	17.8	20.9	37.6	280	70.89	290
SNR(dB)	16.9	19.9	30.3	290	62.80	300
CNR	13.8	16.8	27.0	197	69.67	200
WSNR(dB)	16.8	17.8	29.1	159	70.09	167
VSNR(dB)	16.6	18.8	39.1	176	79.08	180
NQM	15.6	11.6	19.1	275	60.87	280
UQI	0.21	0.42	0.60	132	0.99	140
IFC	9.12	9.99	20.6	283	60.89	289
SSIM	0.24	0.33	0.55	440	0.98	450
MSSIM	0.16	0.18	0.38	233	0.99	236
FSIM	0.15	0.19	0.39	340	0.98	345
RFSIM	0.32	0.34	0.45	320	0.98	323
VIF	10.24	12.56	23.23	330	70.09	332
VIFP	9.78	10.1	18.2	233	67.89	234
MAE	19.2	16.54	11.67	201	2.98	210
AMBE	15.5	13.56	10.45	374	3.67	380

Table 3 MATLAB IQA measures calculations for the image: Brain Phantom. Computational Times observed for High contrast, towards histogram equalization; and for fully High contrast, histogram equalized image.

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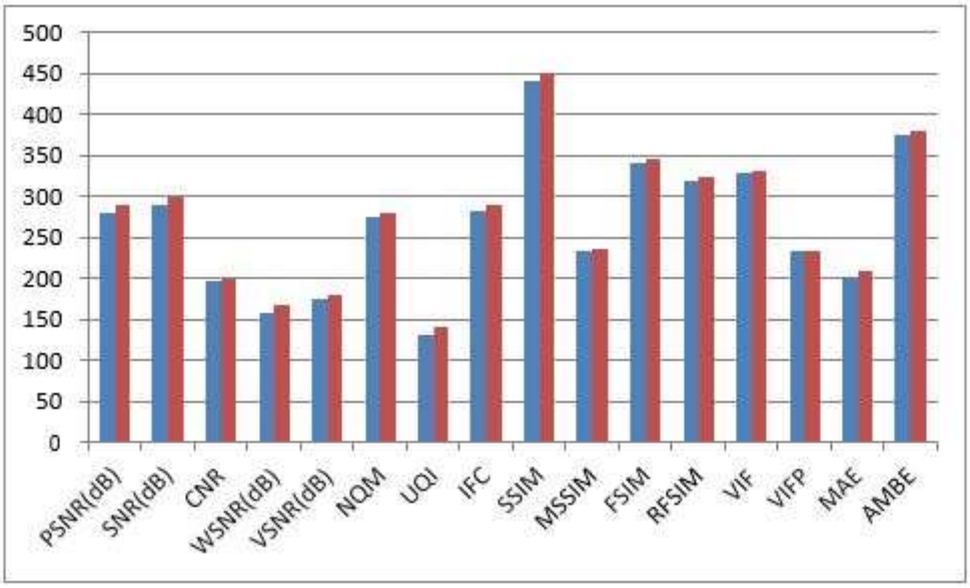

Figure 8 MATLAB computational time Performance for the image: Brain Phantom. Computational Times observed for High contrast, towards histogram equalization (first bar); and for fully High contrast, histogram equalized image (second bar). We can observe that computational time for fully high contrast is more.

Image contrast enhancement performance metric	Low contrast(dark) w.r.t. original image	Low contrast (bright) w.r.t. original	High Contrast (histogram Towards equalization)	Computational time for High contrast image (In ms)	Fully High Contrast (histogram Equalized)	Computational time for Fully High contrast image (In ms)
PSNR(dB)	16.7	19.9	29.6	255	67.15	260
SNR(dB)	15.9	18.6	31.3	300	67.09	310
CNR	12.8	14.8	27.9	201	65.89	203
WSNR(dB)	15.8	16.8	30.1	170	79.98	177
VSNR(dB)	17.6	19.7	38.1	185	82.30	189
NQM	14.6	10.6	18.1	210	50.89	240
UQI	0.19	0.33	0.54	150	0.97	160
IFC	8.97	10.78	16.8	289	56.78	294
SSIM	0.33	0.42	0.59	450	0.99	456
MSSIM	0.18	0.19	0.39	240	0.97	246
FSIM	0.16	0.18	0.38	344	0.98	349
RFSIM	0.33	0.35	0.59	323	0.97	328
VIF	11.24	14.56	29.23	333	68.90	339
VIFP	8.78	11.1	19.2	234	60.78	238
MAE	21.2	18.54	13.67	209	4.56	213
AMBE	22.5	18.56	10.45	360	2.35	370

Table 4 MATLAB IQA measures calculations for the image: Cycle tree cave. Computational Times observed for High contrast, towards histogram equalization; and for fully High contrast, histogram equalized image.

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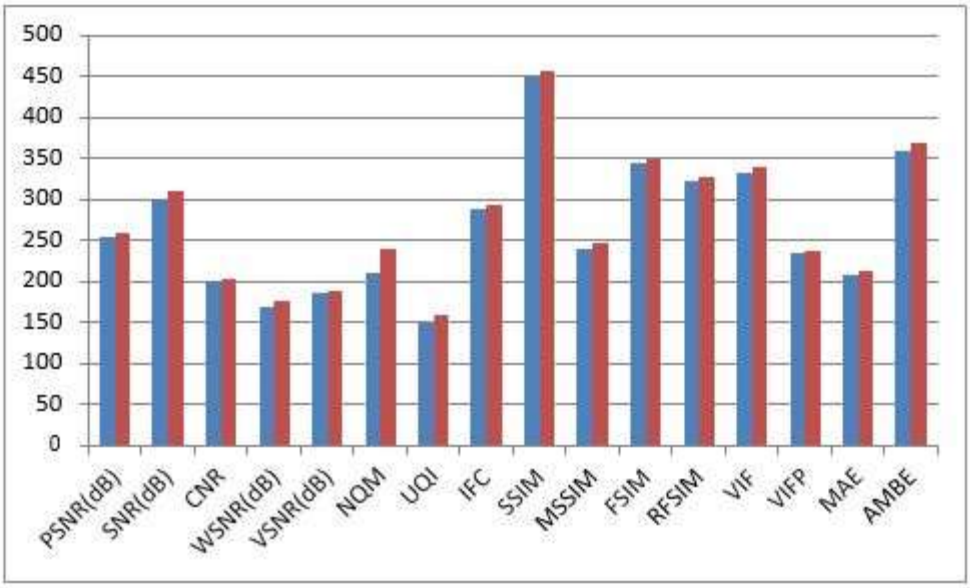

Figure 9 MATLAB computational time Performance for the image: Cycle tree cave. Computational Times observed for High contrast, towards histogram equalization (first bar); and for fully High contrast, histogram equalized image (second bar). We can observe that computational time for fully high contrast is more.

Image contrast enhancement performance metric	Low contrast(dark) w.r.t. original image	Low contrast (bright) w.r.t. original	High Contrast (histogram Towards equalization)	Computational time for High contrast image (In ms)	Fully High Contrast (histogram equalized)	Computational time for Fully High contrast image (In ms)
PSNR(dB)	15.6	18.9	31.2	250	69.89	259
SNR(dB)	13.8	16.6	30.3	319	69.78	324
CNR	11.8	15.8	29.6	210	70.0	219
WSNR(dB)	15.6	15.9	38.9	182	78.98	187
VSNR(dB)	16.6	19.9	37.1	195	75.67	198
NQM	15.9	11.6	19.1	252	60.09	260
UQI	0.29	0.39	0.59	164	0.98	170
IFC	7.78	11.79	18.4	283	50.67	289
SSIM	0.22	0.29	0.56	460	0.99	465
MSSIM	0.17	0.2	0.45	252	0.98	256
FSIM	0.19	0.21	0.42	360	0.97	367
RFSIM	0.32	0.39	0.57	380	0.98	387
VIF	10.27	13.57	28.24	387	69.89	393
VIFP	9.77	10.1	12.6	191	58.90	198
MAE	22.3	18.55	12.66	192	2.45	200
AMBE	19.5	16.56	10.98	294	3.49	298

Table 5 MATLAB IQA measures calculations for the image: Tajmahal. Computational Times observed for High contrast, towards histogram equalization; and for fully High contrast, histogram equalized image.

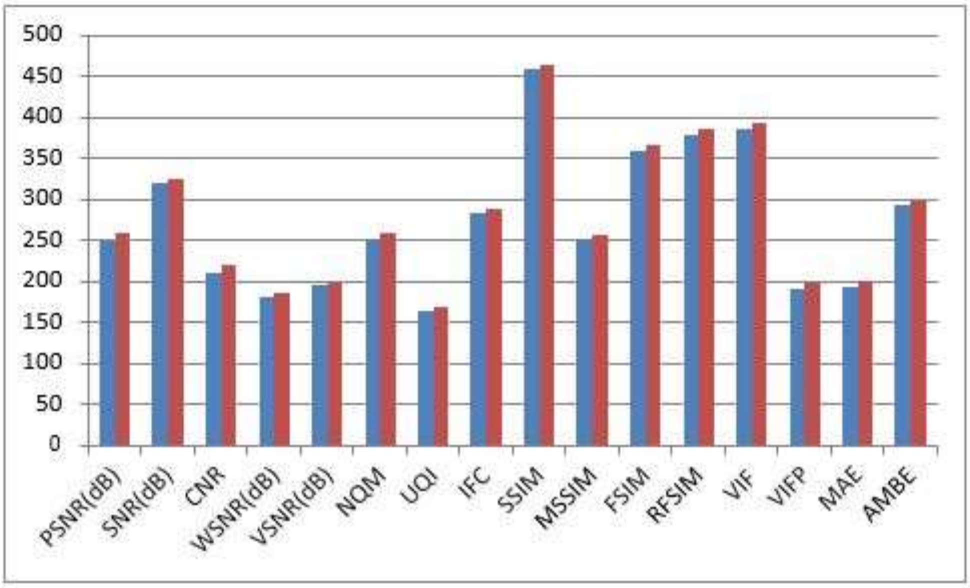

Figure 10 MATLAB computational time Performance for the image: Tajmahal. Computational Times observed for High contrast, towards histogram equalization (first bar); and for fully High contrast, histogram equalized image (second bar). We can observe that computational time for fully high contrast is more.

In this research we did programming using MATLAB 8.3 R2014a. Here we considered 13 different images for the assessment of two novel metrics under evaluation for image contrast enhancement. Here the way we considered these measures in such a way of images of various levels of high contrast. We considered images for low contrast (dark), Low contrast (bright), and images of high contrast of different levels of contrast one is partially high contrast in the sense that towards histogram equalization, and fully high contrast images which are histogram equalized images. The two novel techniques are Histogram Flatness Measure (HFM) and Histogram Spread (HS). Here we are providing histograms and towards equalization histograms for only 3 images as examples for description purposes from Figure 1 to Figure 6. In Figure 7 we provided all the images we considered for this research. The results of the observations of HFM and HS are tabulated in Table 1 and Table 2 respectively. As per the theory of HFM explained in section II, it is clear that low contrast images must have low value of HFM. But if we observe the Table 1, it is observed that for some of the images we are getting high values of HFM even in the case of low contrast images than original images. As per theory explained in section II for HS, it is also true that in case of HS also low contrast images get low value of HS with respect to original image. From the Table 2, for all the considered images we could clearly observe that low contrast images are getting low values of HS and high contrast images are getting high values of HS. Hence HS may work as a cutoff metric between low contrast and high contrast images and hence we can develop the standard notion "High contrast high value and low contrast low value". After assessing HFM and HS, we considered various Image Quality Assessment (IQA) measures for all the images under test. Instead of providing IQA values of all the images under test, here we tabulated the IQA measures for only 3 images: Brain Phantom, Cycle tree cave, Tajmahal images in Table 3, Table 4, and Table 5 for description purposes as example results. Here we can easily observe that basing on contrast increase the values of Peak Signal–to-Noise-Ratio (PSNR), Signal to Noise Ratio (SNR), Contrast to Noise Ratio (CNR), Universal Quality Index (UQI), Noise Quality Measure (NQM), Structural SIMilarity (SSIM), Mean SSIM(MSSIM), Information Fidelity Criterion(IFC), Visual Information Fidelity (VIF), Visual Information Fidelity in Pixel Domain (VIFP), Visual Signal-to-Noise Ratio (VSNR), Wavelets Based SNR (WSNR), Feature similarity Metric (FSIM), Riesz Transform FSIM (RFSIM) are increasing. Mean Absolute Error (MAE), Absolute Mean Brightness Error (AMBE) are decreasing. Here we can make a clear observation that a partially high contrast image is having less values of Peak Signal–to-Noise-Ratio (PSNR), Signal to Noise Ratio (SNR), Contrast to Noise Ratio (CNR), Universal Quality Index (UQI), Noise Quality Measure (NQM), Structural SIMilarity (SSIM), Mean SSIM(MSSIM), Information Fidelity Criterion(IFC), Visual Information Fidelity (VIF), Visual Information Fidelity in Pixel Domain (VIFP), Visual Signal-to-Noise Ratio (VSNR), Wavelets Based SNR (WSNR), Feature similarity Metric (FSIM), Riesz Transform FSIM (RFSIM) when compared to fully high contrast images. From these values we can be clear that how far away or how near from the fully high contrast image is this given partially high contrast image. If it is far away from the fully high contrast image we can be cautious to preserve the image carefully to avoid any further noisy conditions. This situation can be applicable to

preserve partially high contrast images of biomedical images, cosmological images. We have calculated computational times for all the IQA measures for partially high contrast and fully high contrast images. He we can observe that some of these IQA measures are taking less time when compared to others, which is highly useful result when we are implementing Digital Image Processing hardware. In such situation if we need to implement basing on various tradeoffs basing on the constraints of software and hardware of the implementation and speed, area constraints of the implementation, we can choose the best IQA measure for cost effective and speed, area, power constraint DIP processor. Such application is highly useful in high speed, cost effective, highly reliable implementations of real time biomedical micro devices. One more observation we can make from the Table 3, Table 4 and Table 5 is partially high contrast (towards histogram equalization) images are having low value of computational time when compared to the time taken by full high contrast images. This observation can be highly useful when partially high contrast images are sufficient for the application than fully high contrast images, so that in such applications where we can implement high speed Digital Image Processor by utilizing partially high contrast images, instead of fully high contrast images. The computational time analysis is done in bar graphical format in Figure 8, Figure 9, and Figure 10 for direct visual observation and ease of observation. It is clear that fully high contrast images are taking much time.

CONCLUSION & FUTURE RESEARCH

Here we considered two novel techniques HFM and HS for image contrast enhancement. HS is found to be highly consistent. Then we observed various Image Quality Assessment measures for all the images under test. We calculated computational time for all the IQA metrics for all the images. Here in this research we may come to the following 5 conclusions: (1) HS is highly consistent and we may develop the standard notion "high contrast high value, low contrast low value". (2) HS works as a cutoff between low contrast images and high contrast images and highly useful for whether to enhance the image or not. (3) Computational time for all the IQA measures found to be useful in implementing best optimized speed, cost-effective, area, and power utilizing digital image processor for real time biomedical micro devices. (4) Partially high contrast images are taking less computational time than fully high contrast images. This result is highly useful in applications of implementation of high speed Digital Image Processor micro device where partially high contrast images are sufficient. (5) Basing on the IQA values of the images, we can observe that how far in contrast the given high contrast image is with respect to fully contrast image so that, if too far away from fully high contrast image we can be cautious to preserve the image carefully to avoid any exposure to further noise. Such observation is highly useful in biomedical images, cosmological images.

As far as the future research concerned we would like to implement the HS hardware design in Xilinx FPGAs, standard Cell based custom design and would like to observe the tradeoffs in design and implementation in terms of speed, area and power utilization.

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CONFLICT OF INTEREST

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

REFERENCES

1. Rafael C Gonzalez and Richard E Woods, "Digital Image Processing", third edition, Pearson Education,2007.
2. J. A. Stark, "Adaptive Image Contrast Enhancement Using Generalizations of Histogram Equalization," IEEE Transactions on Image Processing, 9(5), pp.889-896, 2000.
3. S.-D. Chen, A. Ramli, "Minimum mean brightness error bi histogram equalization in contrast enhancement," IEEE Trans. on Consumer Electronics, vol. 49, no. 4, pp. 1310-1319, Nov. 2003.
4. Fan-chieh cheng" Color Contras enhancement Using Automatic Weighting Mean-Separated Histogram Equalization "International journal of innovative Computing ,information and control,Vol.7,No.9,2011.
5. J. A. Stark, "Adaptive Image Contrast Enhancement Using Generalizations of Histogram Equalization," IEEE Transactions on Image Processing, 9(5), pp.889-896, 2000.

6. Vijay A. Kotkar, Sanjay S. Gharde, "REVIEW OF VARIOUS IMAGE CONTRAST ENHANCEMENT TECHNIQUES", International Journal of Innovative Research in Science, Engineering and Technology Vol. 2, Issue 7, July 2013
7. Vinay Kumar and HimaniBansal, "Performance Evaluation of Contrast Enhancement Techniques for Digital Images", International Journal of Computer Science and Technology, Vol. 2, No. 1, pp.23-27, 2011.
8. Trivedi, J anupam, V Bhateja "A Novel HVS Based Image Contrast Measurement Index", M., ICSIP 2012.
9. Tripati AK, Mukhopadyay, Dhara AK, "Performance metrics for image contrast", IEEE, ICIIP 2011.
10. Narayanam Ranganadh, L Koteswara rao, "Development of a novel standard notion for the image contrast enhancement performance measure, International Journal of Engineering Sciences and Research Technology, 2015.
11. Atma K, Sos A, Karen P, "NEW CONTRAST MEASURE FOR TRANSFORM BASED IMAGE ENHANCEMENT", ticsp, tufts university, 2011.
12. Shruti P, Sankalp A, "Performance evaluation of image enhancement techniques", IJSIPPR, Vol 8(8),2015.
13. Susan SY, Ronald GD, Eddie LJ, "Signal Processing and Performance Analysis for Imaging Systems", text book, ARTECH HOUSE, 2008. [14] C.Bajaj Tutorial Notes on "Multiscale, Bio-Modeling and Visualization", Chap 2, 2010.