# Enhancement of the low contrast image using fuzzy set theory

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***Abstract*—This paper presents a fuzzy grayscale enhancement technique for low contrast image. The degradation of the low contrast image is mainly caused by the inadequate lighting during image capturing and thus eventually resulted in nonuniform illumination in the image. Most of the developed contrast enhancement techniques improved image quality without considering the nonuniform lighting in the image. The fuzzy grayscale image enhancement technique is proposed by maximizing fuzzy measures contained in the image. The membership function is then modified to enhance the image by using power-law transformation and saturation operator. The qualitative and quantitative performances of the proposed method are compared with the other methods. The proposed method produced better quality enhanced image and required minimum processing time than the other methods.**

***Keywords-nonuniform illumination; fuzzy; grayscale; enhancement; overexposed image; underexposed image***

## I. INTRODUCTION

Good contrast images with preserving details are required for many important areas namely machine vision, remote sensing, dynamic and traffic scene analysis, biomedical image analysis and autonomous navigation. However most of the recorded images suffer from poor contrast which is due to the inadequate lighting during image acquiring, wrong setting of aperture size and shutter speed as well as nonlinear image intensities mapping.

Difficulties in controlling the lighting conditions during image acquisition process have resulted in variability in image illumination. The captured images turn out to be low contrast and contained underexposed and overexposed regions.

Thus, image enhancement has been employed to increase the quality of the image. Image enhancement is a fundamental task applied in image processing to improve interpretability and appearance of the image. It provides better input image for further image processing task.

Image enhancement can be clustered into two groups namely frequency domain and spatial domain methods. In the frequency domain method, the enhancement is conducted by modifying the frequency transform of the image. Meanwhile in the latter method, image pixels are directly modified to enhance the image. However, computing the enhancement in frequency domain is time consuming process even with fast transformation technique thus made it unsuitable for real time application [1].

Numerous contrast enhancement techniques normalized the image intensities and often fail to produce satisfactory results for a broad range of non-uniform illumination image. The image is characterized by the fact that the amplitudes of their histogram components are very high at one or several locations on the grayscale, while they are very small, but not zero, in the rest of the grayscale. This makes it difficult to increase the image contrast by simply stretching its histogram. The high amplitude of the histogram components also often prevents the use of the histogram equalization (HE) techniques. Most of the HE techniques could cause a washed-out effect on the appearance of the enhanced image and/or amplify existing noises [2].

In addition, due to the poor and low contrast nature of the acquired image, vagueness and ambiguity are introduced and have led to the increment of uncertainty in the image information. This vagueness in the image appears in the form of imprecise boundaries and intensities during image digitization.

Therefore, fuzzy sets theory [3] has been proposed as a problem solving tool between the precision of classical mathematics and the inherent imprecision of the real world. The imprecision possessed by the acquired image can be perceived qualitatively by human reasoning. However, there is no specific quantification to describe the imprecision and thus machine may not understand them. Realizing this limitation to a great extent, fuzzy logic tools empower a machine to mimic human reasoning.

In the image enhancement field, the fuzzy set theory has been widely utilized by other researchers [1, 4-17]. Pixel property such as gray tone intensity is modeled into a fuzzy set using a membership function. The image is considered as an array of fuzzy singletons having a membership value that denotes the degree of belonging to specific property.

The conventional method of fuzzy enhancement is conducted by using contrast intensification (INT) operator [3]. In this method, dynamic range of image is possible to be obtained since the INT operator will increase and decrease the membership degree above and below threshold value respectively. However, the INT is solely depended on the membership function and it needs to be applied continuously on the image to attain desired enhancement.

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This limitation is then improved by [7] using new intensification operator (NINT) which utilized sigmoid function. The NINT does not change uniformly because the membership function is marginally changing, thus computational time can be reduced as compared to the INT.

The other enhancement approach is conducted using fuzzy rule-based technique [18-20] which human intuition is incorporated to make soft decisions on each condition. This method suffers from high computational time and thus made it difficult to automatically generate fuzzy rules. In addition, prior threshold selection needs to be done for each condition and therefore made choosing the optimum threshold could be challenging.

Image enhancement is also done by measuring information contained in the image [11, 13, 21, 22]. The membership function is chosen based on the measured quantity such as image entropy or index of fuzziness. An optimum quantitative measure has to be determined in order to achieve best enhancement quality.

In addition, attempts have been made to enhance the image locally [6, 12, 23]. In this technique, local contrast in small regions is enhanced while at the same time preventing an increase in global contrast. Fine edges which are neglected in global enhancement are enhanced and clarity of the enhanced image is improved. However, noises and artifacts might also be enhanced during the enhancement process.

In this paper, a new contrast enhancement technique has been proposed by minimizing fuzziness in the image without requiring complex procedure and long computational time.

## II. The Proposed Technique

The original image of size *M* x *N* has intensity levels $m_{i,j}$ in the range of *[0 L-1]* can be considered as a collection of fuzzy singletons in the fuzzy set notation.

$$I = \bigcup\{\mu(m_{i,j})\} = \{\mu_{i,j} / m_{i,j}\} \quad i = 1,2,\ldots, M;\ j = 1,2,\ldots, N \tag{1}$$

where $\mu(m_{i,j})$ or $\mu_{i,j}/m_{i,j}$ represents the membership or grade of belonging $\mu_{i,j}$ of $m_{i,j}$ being the grayscale intensity at the *(i,j)* th pixel.

### A. Fuzzy Measures

Let *I* be a set with randomly gray level values $\{m_{i,j}$ *at (i,j) th pixel*$\}$ and $\{p_0, p_1, p_2 \ldots p_{L-1}\}$ are respective probabilities of gray level values. The fuzzification of set *I* induced two kinds of uncertainties. The first part of uncertainties induced by the random nature of the image given by:

$$H = -\sum_{k=0}^{255} p_k \log(p_k) \tag{2}$$

Meanwhile second uncertainty arises from the fuzziness of the fuzzy set related to the ordinary set given by:

$$J = -\mu_k \log(\mu_k) - (1-\mu_k)\log(1-\mu_k) \tag{3}$$

Therefore, the total entropy, *E* is expressed by:

$$E = H + J \tag{4}$$

The index of fuzziness (IOF) is calculated using equation (5) as follow:

$$IOF = \frac{2}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\min\{p_{i,j},(1-p_{i,j})\} \tag{5}$$

where

$$p_{i,j} = sim\left[\frac{\pi}{2}\times(1-\frac{\mu(m)}{\mu_{\max}})\right] \tag{6}$$

### B. Membership Function Calculation

The shape of S-function is commonly used for the representation of the degree of brightness or whiteness of pixels in the grey levels images. The S-function was originally introduced by [2] and the definition of more flexible S-function was proposed by [23]. The flexible S-function has been adapted in this study to fuzzify the original image.

$$\mu(m) = \begin{cases} 0 & for\ m \le a \\ \dfrac{m-a}{(b-a)(c-a)} & for\ a < m \le b \\ 1 - \dfrac{(m-c)^2}{(c-b)(c-a)} & for\ b < m \le c \\ 1 & for\ m \ge c \end{cases} \tag{7}$$

where *m* is the intensity of the image and *a, b* and *c* are parameters that determined the shape of the S-function. The parameters *a, b* and *c* are specified to ensure the membership function maximizes the information contained in the image. It is done by incorporating two fuzzy measures namely fuzzy entropy and index of fuzziness.

Therefore parameters *a, b* and *c* are given by equations (8) to (10).

$$a = \alpha E_{\max} \tag{8}$$

$$b = \beta\left|IOF_{\max} - E_{\max}\right| \tag{9}$$

$$c = \gamma IOF_{\max} \tag{10}$$

where $\alpha$ , $\beta$ and $\gamma$ are the membership factors that are chosen to obtain optimum S-membership function if fuzzified image. $IOF_{max}$ and $E_{max}$ are maximum index of fuzziness and maximum entropy respectively.

The calculated membership function transformed the image intensity levels from the spatial domain to fuzzy domain. The original image has been transformed and most of the regions in the image contained mixed region of overexposed and underexposed regions. Therefore, a parameter called 'exposure' is introduced to denote percentage of the image gray levels is underexposed and overexposed. The exposure denotes an amount of intensity exposition is given by [1]:

$$Exposure = \frac{1}{L}\left[\frac{\sum_{m=1}^{L} p(m)*m}{\sum_{m=1}^{L} p(m)}\right] \quad (11)$$

where $L$ is number of gray levels of the image meanwhile $p(m)$ and $m$ are histogram and gray level values of the image respectively. The exposure is normalized in the range of $[0\ 1]$. If the value of exposure is less than $0.5$, it denotes that the image contains more underexposed region than overexposed region.

The threshold is determined to divide the image into two parts. The threshold is given by equation (12)

$$T = \theta L(1\text{-}Exposure) \quad (12)$$

where $T$ and $\theta$ are threshold and exposure operator respectively. The exposure operator, $\theta$ is defined to obtain optimum threshold for enhancement. The threshold, $T$ which is in the range $[0\ L\text{-}1]$ divides the gray levels into two regions which are $[0,\ T\text{-}1]$ for underexposed region and $[T,\ L\text{-}1]$ for overexposed region.

The membership function (*i.e* fuzzified image) is then modified to further enhance the fuzzified image.

$$\mu_{enh} = \begin{cases} \sqrt{\tau\mu(m)} & for\ \mu(m) < T \\ [\mu(m)]^2 & for\ \mu(m) \geq T \end{cases} \quad (13)$$

where $\tau$ is the enhancement factor that is used to enhance the image.

It is known that the gray levels of the image are heap near the maximum gray level and minimum gray level for overexposed and underexposed regions respectively. A power-law transformation operator is defined for the improvement of the overexposed region of the image. The intensities of the membership function in overexposed region are improved by modifying their membership function in this region.

Meanwhile the underexposed regions have the exposure values less than 0.5 and thus only need a gradual amount of saturation enhancement. The membership function is modified using saturation operator of square root as given by equation (13). Modification of saturation restores the pleasing nature for such images.

## III. DATA ANALYSIS

The proposed method has been implemented on Intel Core 2 CPU 2GHz using Matlab R2010b. 100 standard images (size: 400x264) obtained from California Institute of Technology database which consist of underexposed and overexposed regions are considered as test images.

The enhanced image is analyzed in terms of its output quality and quantitative analysis such as index of fuzziness (IOF), image contrast (C) peak signal to noise ratio (PSNR) and processing time.

In addition, the performance of the proposed algorithm is compared qualitatively and quantitatively with other state of the art methods namely conventional approach of NINT [3], application of fuzzy IF-THEN rules (fuzzy rule-based) [17], fuzzy quantitative measure [10] and fuzzy local enhancement [5] are widely used in image enhancement. The techniques in those literatures are selected since they involved in enhancing image contrast in fuzzy domain. Each of method has been discussed in Introduction part.

For the subjective evaluation in terms of the image quality, the enhanced image is expected to be brighter than the original image without overenhancing overexposed region and/or underenhancing underexposed region.

Furthermore, the applied enhancement method should minimize the uncertainty in image information. Thus, *IOF* is employed to measure the degree of fuzziness (*i.e* uncertainty) in the image. A smaller *IOF* indicates a better performance of image enhancement. In addition, the method should not significantly amplify the noise level and thus a high value of *PSNR* is required. Furthermore, the enhanced image must obtain optimum image contrast *(C)* to distinguish between the object and the background. The contrast for enhanced image ought to be close to the contrast of the original image to attain good image quality. The *PSNR* and $C$ are calculated using equations (14) to (15) respectively. The *IOF* is calculated using equation (5).

$$PSNR = 10\log_{10}(L-1)^2 / MSE \quad (14)$$

$$C = \sqrt{\sum_{m=0}^{L\text{-}1}(m - m_{avg})^2\, p(m)} \quad (15)$$

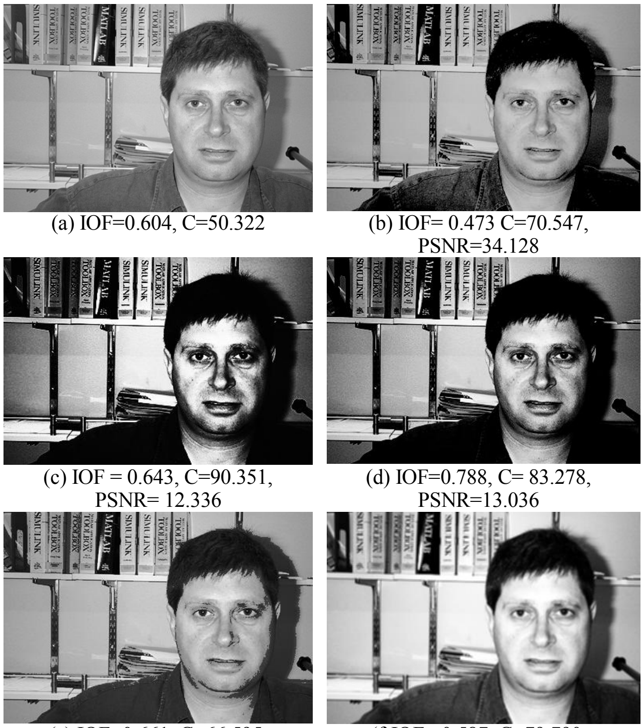
where

$$MSE = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(\mu_{i,j} - m_{i,j}\right)^2}{M*N}} \quad (16)$$

## IV. RESULT AND DISCUSSIONS

The enhanced images produced by the proposed and other methods are presented in Figures 1 to 4. For the subjective qualitative analysis of processed image appearance, the test images namely ‘Man 1’, ‘Woman’, ‘Man 2’and ‘Man 3’ are shown in these figures. The original images have poor brightness in the underexposed regions and brightness is higher in the overexposed regions.

The NINT (Figures 1(c), 2(c), 3(c) and 4(c)) and fuzzy quantitative measure (Figures 1(d), 2(d), 3(d) and 4(d)) underenhanced the original image and thus resulted in darker image as compared to the original image. The processed images by both methods tend to underenhanced the region at the center of the image. This is because the both methods processed the whole image without taking into consideration the information (*i.e* exposure) contained in the image. Therefore it has led to the uneven and unnatural enhanced image



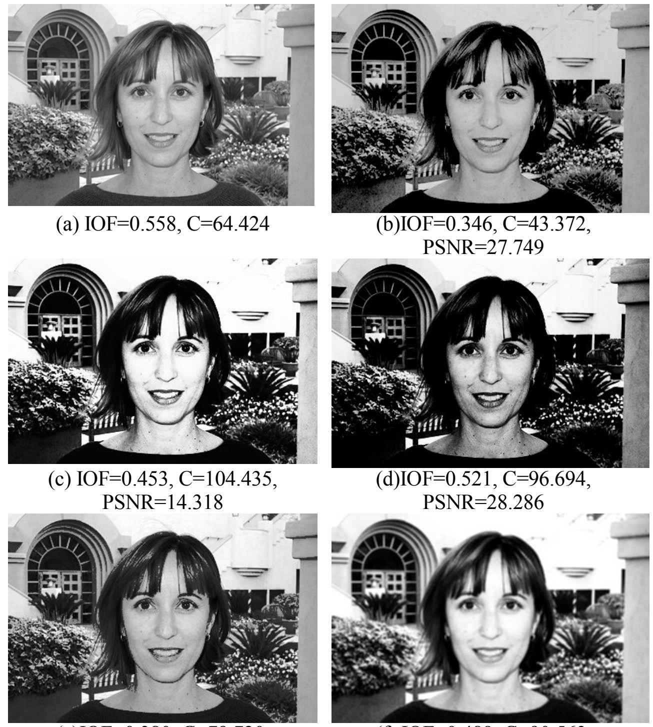
(a) IOF=0.604, C=50.322
(b) IOF= 0.473 C=70.547, PSNR=34.128
(c) IOF = 0.643, C=90.351, PSNR= 12.336
(d) IOF=0.788, C= 83.278, PSNR=13.036
(e) IOF=0.661, C=66.595, PSNR= 19.867
(f)IOF= 0.587, C=79.790, PSNR=16.797

Figure 1: (a) original image (Man 1), enhanced image with (b) proposed method (c) NINT (d) quantitative measure (e) fuzzy rule-based (f) fuzzy local enhancement

Meanwhile the fuzzy rule-based and local fuzzy enhancement overenhanced the original image and thus led to the unnecessary increment in brightness around man's or woman's face.

In addition, the figures depict that the fuzzy-rule based and fuzzy local enhancement produced the overenhanced regions mostly at the center of the images. The fuzzy local enhancement has increased the contrast in local neighbourhoods in the images and revealed the fine details in the image. Furthermore, the fuzzy local enhancement able to avoid intensity saturation as compared to the fuzzy rule-based technique. The fuzzy rule-based technique caused the intensities saturations near Man 1's face and Woman's hair in Figures 1 (e) and 2(e) respectively. Thus, enhancement of those images may contain additional noises due to the unnecessary saturation.

The enhanced images (*i.e* Figures 1(b), 2(b) and 3(b)) obtained by the proposed method are more pleasant and the brightness of the image is improved accordingly with their respective regions. In the proposed method the intensities of the underexposed regions are increased by saturation operator and thus made it brighter than the original image. Meanwhile the intensities of overexposed regions are decreased by power-law transformation and resulted in decrement in intensity values. Therefore dynamic range of enhanced image is obtained and image contrast is preserved.



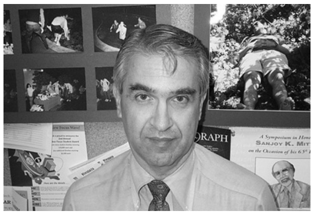
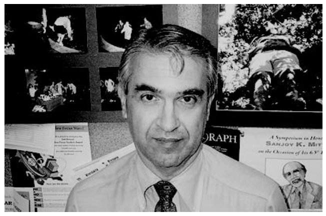
(a) IOF=0.558, C=64.424
(b)IOF=0.346, C=43.372, PSNR=27.749
(c) IOF=0.453, C=104.435, PSNR=14.318
(d)IOF=0.521, C=96.694, PSNR=28.286
(e)IOF=0.380, C=79.720, PSNR=19.289
(f) IOF=0.489, C=90.563, PSNR=16.861

Figure 2: (a) original image (Woman), enhanced image with (b) proposed method (c) NINT (d) quantitative measure (e) fuzzy rule-based (f) fuzzy local enhancement

The enhanced images by proposed method are quite similar to the enhanced images by fuzzy rule-based. However, the fuzzy rule-based has overenhanced existing overexposure region at the top corner of the original images as shown in Figures 2 (e) and 3 (e). The proposed method seems able to identify the existing overexposed region and thus reduce the pixel value by using power-law transformation.

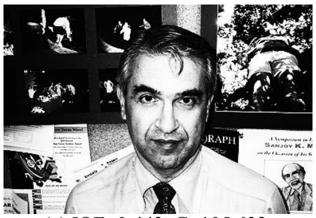
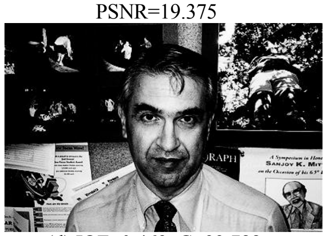
The qualitative analysis presented in the Figures 1 to 4 can be supported by quantitative analysis presented in Table 1. The average analysis for 100 standard images of proposed method, NINT, fuzzy rule-based, fuzzy quantitative analysis and fuzzy local enhancement presented in Table 1 are discussed. For each analysis, the best results obtained are made bold.

Table 1 indicates that the proposed method has the best performances in terms of smallest *IOF*, highest *PSNR* and obtained good contrast. However, in terms of the average execution time, NINT has the fastest processing time because NINT is less complex and treated the whole image as mixed region without considering overexposed and underexposed regions.

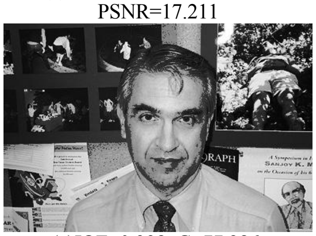
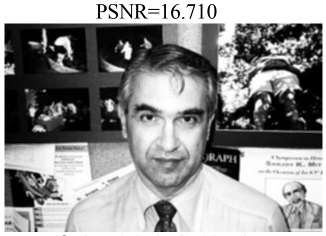
(a)IOF=0.472, C=64.005

(b)IOF=0.341, C=81.424, PSNR=19.375

(c) IOF=0.443, C=105.632, PSNR=17.211

(d) IOF=0.463, C=93.788, PSNR=16.710

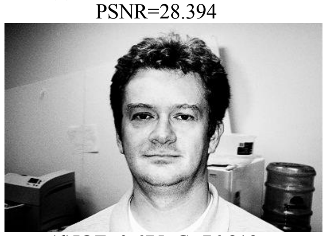
(e)IOF=0.398, C=77.286, PSNR=19.789

(f)IOF=0.359, C=92.565, PSNR=18.089

Figure 3: (a) original image (Man 2), enhanced image with (b) proposed method (c) NINT (d) quantitative measure (e) fuzzy rule-based (f) fuzzy local enhancement


(a)IOF=0.686, C=36.100

(b)IOF=0.503, C=48.372, PSNR=28.394

(c) IOF=0.564, C=90.541, PSNR=8.013

(d)IOF=0.675, C=76.819, PSNR=13.758


(e)IOF=0.651, C=49.310, PSNR=22.210

(f)IOF=0.511, C=53.015, PSNR=16.680

Figure 4: (a) original image (Man 4), enhanced image with (b) proposed method (c) NINT (d) quantitative measure (e) fuzzy rule-based (f) fuzzy local enhancement

The fuzzy-rule based needs the longest time to be executed since the decision can only be made if the previous condition is performed. Besides that, the fuzzy local enhancement required longer time to be executed since enhancement process is done locally using overlapping window over entire image.

The proposed method attained smallest *IOF* which indicates that the degree of fuzziness in the enhanced images is lowest as compared to the other enhanced images produced by other methods. The enhanced images by proposed method became more interpretable since the *IOF* of the enhanced images is decreased from the *IOF* of the original images (*i.e* average value of *IOF* obtained from original images = 0.461).

In addition, the proposed method achieved highest *PSNR* among other methods which concludes that the proposed method does not amplify existing noise in the original image. Even though the NINT only requires minimum time to be executed, it has increased the existing noises and artifacts possessed by the original image and thus resulted in the lowest value of PSNR.

TABLE I. QUANTITATIVE ENHANCEMENT ANALYSES FOR 100 STANDARD IMAGES (AVERAGE VALUES)

| Method\Analysis | Processing Time, t (s) | IOF | PSNR (dB) | C |
|---|---|---|---|---|
| Proposed Method | 0.062 | **0.349** | **22.039** | **71.969** |
| NINT | **0.050** | 0.443 | 13.947 | 88.391 |
| Fuzzy rule-based | 11.921 | 0.367 | 19.096 | 78.793 |
| Fuzzy Quantitative Measure | 0.063 | 0.410 | 15.417 | 82.654 |
| Fuzzy Local Enhancement | 11.163 | 0.584 | 19.063 | 81.929 |

Table 1 also indicates that the image contrast of the proposed method is the lowest and closer to the average contrast of original images which is 55.814. The absolute difference between the average of image contrast by proposed method and the average of those original images contrast is the smallest as compared to the other methods. This is because the produced images by proposed method are better in preserving the contrast of the original images. Thus, it can be concluded, the enhanced image from the proposed method is more natural and image intensities are not saturated.

## V. CONCLUSIONS

The new enhancement technique using fuzzy set theory has been developed for grayscale non-uniform illumination image. Findings signified that the proposed method produced better image quality and defeated other methods in terms of image contrast and measure of fuzziness without enhancing existing noise in the image. The proposed algorithm only required minimum processing time (*i.e* approximately 62ms) and thus made it as suitable approach to be used in the real time application.

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