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Adaptive fuzzy contrast factor enhancement technique for low contrast and nonuniform illumination images

Khairunnisa Hasikin · Nor Ashidi Mat Isa

Abstract This paper presents a new enhancement technique using the fuzzy set theory for low contrast and nonuniform illumination images. A new parameter called the contrast factor which will provide information on the difference among the gray-level values in the local neighborhood is proposed. The contrast factor is measured by both local and global information to ensure that the fine details of the degraded image are enhanced. This parameter is used to divide the degraded image into bright and dark regions. The enhancement process is applied on gray-scale images wherein the modified Gaussian membership function is employed. The process is performed separately according to the image's respective regions. The performance of the proposed method is comparable with other state-of-the-art techniques in terms of processing time. The proposed method exhibits the best performance and defeats other methods in terms of preserving brightness and details without amplifying existing noises.

Keywords Nonuniform illumination · Underexposed · Overexposed · Bright · Dark · Contrast factor

K. Hasikin · N. A. Mat Isa (✉)
Imaging and Intelligent System Research Team (ISRT),
School of Electrical and Electronic Engineering,
Engineering Campus, Universiti Sains Malaysia,
14300 Nibong Tebal, Penang, Malaysia
e-mail: ashidi@eng.usm.my

K. Hasikin
Department of Biomedical Engineering, Faculty of Engineering,
University of Malaya, 50603 Lembah Pantai, Kuala Lumpur, Malaysia
e-mail: khairunnisa@um.edu.my

1 Introduction

The visual quality of the most recorded images is inevitably degraded during the image acquisition process because of inadequate lighting and incorrect setting of the aperture or the shutter speed or both. Deficiencies in the image acquisition process often result in low contrast images which normally contain noisy backgrounds. In addition, difficulties in controlling lighting conditions lead to variation in image illumination and thus causing the nonlinear gray-scale intensity mapping. The effects of those defects are replicated on the range and shape of the gray-level histogram of the acquired image.

A low contrast image is characterized by the high amplitudes of its histogram components at one or several locations on the gray-scale, while staying very low in the remaining gray-scale distributions. As a result, the space for foreground histogram components (i.e., an object of interest) is compressed and image contrast is decreased.

Improving image contrast is difficult by simply stretching the histogram of the image or using simple gray-level transformations. Conventional image enhancement techniques generally obtain satisfactory results if the technique and parameters are properly selected. However, conventional techniques often fail to produce satisfactory results in dynamic and broad range of nonuniform illumination images. Therefore, improving the appearance of the image is essential in providing better input images for further image processing tasks.

Numerous studies have been published on image enhancement or also known as contrast enhancement. However, the concept of image contrast lacks a precise definition and has been interpreted as a qualitative rather than a quantitative measure of an image [1,2]. Uncontrollable deficiencies seldom occurred during the image acquisition process causing

the vagueness and uncertainty in the acquired image. Uncertainty appears in the form of imprecise boundaries and intensities during image digitization.

Therefore, the fuzzy set theory [3–5] has been widely applied by researchers when dealing with the 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 [6] that suitable for image enhancement.

The remainder of this paper is organized as follows. Related studies on the enhancement process are discussed in detail in Sect. 2. The acquired image is categorized based on the new parameter called the contrast factor in Sect. 3. The proposed algorithm for fuzzification and enhancement are presented in Sect. 4. Simulation of the test images and the qualitative and quantitative comparison of the results are discussed in Sect. 5. Finally, this paper is concluded in Sect. 6.

2 Related works

The enhancement process is a preprocessing task needed to obtain a pleasant image. The most popular concept in the enhancement process is based on the modification of the image histogram. This technique is a popular choice among researchers for image enhancement because of its simplicity and capability to produce a good results over variety of images. However, many histogram-based contrast enhancement techniques have normalized image intensity which can produce a washed-out effect [7,8] on the output image or amplify the background noise, or both. Several modified histogram-based contrast enhancement techniques have been proposed to overcome this limitation. These techniques include bi-histogram equalization [9], quadrant dynamic histogram equalization [10], histogram specification [11] and brightness preserving dynamic histogram equalization [12].

These techniques process crisp histograms of images for enhancement purposes. The crisp statistics of digital images suffers from inherent limitation that excludes the inexactness of gray values. Because of this limitation, a dynamic fuzzy histogram equalization with brightness preserving is proposed by Sheet et al. [13] to overcome uncertainty in low contrast images. The fuzzy set theory is employed in this technique to handle the inexactness of gray values wherein

the histogram is partitioned based on local maxima. This equalization method uses a spanning function on the total number of pixels in the partition to perform equalization. However, implementing the fuzzy histogram is challenging on nonuniform illumination images, where bright (overexposed) and dark (underexposed) regions exist in a particular image.

Other approaches which are highly similar to human reasoning that have been applied in image enhancement deal with 'IF-THEN-ELSE' fuzzy rule-based system [14–17]. A set of neighborhood pixels forms the antecedent part of the rule in this method. The pixel to be enhanced is transformed by the consequent part of the rule. This approach incorporates human intuition to make soft decisions on each condition. However, this method suffers from high computational time and difficulty in generating a fuzzy rule. The consequent part of the rule will only be executed if the prior rule is accomplished, thus this technique is difficult to implement in real-time applications.

Besides that, there are other approaches that use several pixel properties such as gray tone or color intensity. These approaches are modeled into a fuzzy set using the membership function. An intensification (INT) operator is applied globally to modify the membership function to reduce fuzziness and increase image contrast [18]. This approach transforms membership values that are above a predetermined threshold to much higher values or modify the membership values that are lower than the threshold value to much lower values in a nonlinear manner. Thus, a dynamic range of images with good contrast can be obtained. However, the INT operator solely depends on the membership function and needs to be continuously applied to the image to attain the desired enhancement.

This limitation is then improved using a Gaussian type of fuzzification function that contains a single fuzzifier and a new intensification operator (NINT) [1]. The fuzzifier is obtained by maximizing the fuzzy contrast. The NINT does not change uniformly because the membership function is marginally changing. Thus computational time is reduced compared with INT.

Although most image enhancement techniques can improve image brightness, several deficiencies are still present in these techniques such as loss of image contrast and details. Thus, various enhancement techniques are proposed by optimizing the information contained in the image which will be used in adjusting gray-level transformation function [19–22]. The optimization of image content includes optimizing entropy [20,23], index of fuzziness [21,24] or a combination of both [25] and intuitionistic fuzzy [20,22].

An objective measure called exposure has been proposed by [26] which will provide an amount of lighting exposure to the image. The image can be divided into underexposed

Fig. 1 Example of underexposed (i.e., *black circle*) and overexposed (i.e., *dotted black circle*) regions

and overexposed regions based on this objective measure. Only a few studies address the issue of nonuniform lighting in an image in the context of image enhancement [26–29]. The objective measure is constructed by involving the entropy, the contrast and visual factor of the image. Minimizing this objective measure successfully enhances an image.

However, the image enhancement process performed by optimizing these quantitative measures requires an optimization procedure that is conducted repeatedly to improve the image quality. Therefore, the process needs a more complicated optimization procedure in addition to the enhancement process which can increase computational time.

Attempts have been made to locally enhance the image to increase image details without involving an additional optimization process [30–34]. The local contrast or local entropy in small regions is enhanced in this technique while preventing an increase in global contrast at the same time. Fine edges neglected in global enhancement are enhanced. The clarity of the enhanced image is improved. However, noises and artifacts are enhanced, and multiplex elements of the background are distorted during the enhancement process.

Realizing the fact, a new contrast enhancement technique has been proposed to improve the brightness of the image by considering nonuniform lighting that normally exists in the acquired image (Fig. 1). The major contribution of this paper is the development of the new enhancement technique that preserves image details by calculating differences in gray-level values in the local neighborhood.

3 Image classification based on contrast factor

Most recorded images suffer from low contrast and appear nonhomogeneous in terms of illumination. The image appears darker and brighter when intensity distribution mainly accumulates at the lower and upper parts of the histogram, respectively. These conditions can be observed in their histograms which do not occupy the entire dynamic range of the intensity distribution. The histogram only occupies a certain area in the lower or upper parts of the total range of the histogram distribution. The image is blurred, poor in contrast and has image details that are hardly interpreted in both cases.

When the recorded image appears dark, its neighborhood pixels are close to the least available dynamic range, and it can be considered as an underexposed image. For a bright image, its neighborhood pixels are found in the highest of available dynamic range and the image is known as an overexposed image.

However, we seldom encounter a solely overexposed (bright) image or a solely underexposed (dark) image. Most of the recorded images are mixed wherein underexposed, overexposed or a combination of both regions are found in one image. As a result, the brightness of image becomes uneven and the image is identified as having nonuniform illumination. This type of image has poor contrast which means that the ratio between the brightest and darkest intensities in the image is reduced. The human perception of the concept of image contrast does not completely correspond to this problem. Therefore, the image contrast is not a preferable reference parameter in enhancing an image.

A new parameter called "contrast factor" is introduced to overcome the aforementioned drawbacks. This parameter indicates the differences among the gray levels for each pixel in the neighborhood window, W_{mn}. The contrast factor is calculated by:

$$\mathrm{CF}_{(Xi,j)} = \frac{\sum_{(i,j)\in W_{i,j}} \left(X_{i,j} - \bar{X}_{W_{i,j}}\right)^2_{i,j\in W_{i,j}}}{\sum_{(i,j)\in W_{i,j}} \sigma^2_{X_{W_{i,j}}}} \tag{1}$$

where $X_{i,j}$ indicates the gray-level values (i.e., intensities) of the image, $\bar{X}_{W_{i,j}}$ represents local average gray level value in the $W_{i,j}$ window and $\sigma^2_{X_{W_{i,j}}}$ represents the local deviation in the $W_{i,j}$ window.

The contrast factor is derived based on the difference in luminance (intensity) with the average of local neighborhood luminance to preserve details in the image. The difference is then divided by the standard deviation of the local neighborhood luminance to obtain an overall difference ratio in the local neighborhood window luminance. The value of contrast factor is between [0 1]. The image looks natural and pleasing if the contrast factor is close to 0.5. The image is low in contrast and should be enhanced if the contrast factor deviates far from 0.5.

The image is considered to be a mixed-type image. Thus attempts have been made to divide the image into overexposed and underexposed regions by introducing a new

threshold, T. This threshold is defined to divide the image into two regions where enhancement is conducted separately according to its respective regions as given in Eq. (2).

$$T = L(1 - \text{CF}) \qquad (2)$$

where L represents the total number of gray levels in an image. The threshold divides the gray levels into two regions namely the dark (i.e., underexposed) region which is in the range $[0, T-1]$ and bright (i.e., overexposed) region which is in the range $[T, L-1]$.

4 Image fuzzification, enhancement and deffuzification

Images from California Institute of Technology database [35] are used for the enhancement purposes in this study. As discussed in Sect. 1, that the image pixels are too vague and uncertain to determine whether they are bright or dark pixels. In addition, the human perception of image contrast is subjective and hard to interpret when machines are used. Therefore, the fuzzy set theory has been employed in dealing with the image pixels ambiguity by associating a degree of belonging to a particular property.

The fuzzy enhancement involves three stages namely image fuzzification, modification of membership values for image enhancement and image deffuzification as shown in Fig. 2. In the image fuzzification stage, the recorded image of size $C \times R$ in the image fuzzification stage has intensity levels $X_{i,j}$ in the range of $[0L-1]$ which is considered as a collection of fuzzy singletons in the fuzzy set notation.

$$I = \cup\{\nu(X_{i,j})\} = \{\nu_{i,j}/X_{i,j}\} \quad i = 1, 2, \ldots, C; \\ j = 1, 2, \ldots, R \qquad (3)$$

where $\nu(X_{i,j})$ or $\nu_{i,j}/X_{i,j}$ represents the membership or grade of belonging $\nu_{i,j}$ of $X_{i,j}$ being the grayscale intensity at the (i, j) th pixel. C and R are the number of rows and columns in the recorded image, respectively.

The original recorded image in the spatial domain will be converted to a fuzzy domain using a specific membership function according to its region (i.e., dark or bright regions). The gray-level histogram in this study is assumed to be distributed in Gaussian where the gray levels are clustered around a single maximum throughout the entire range of the histogram. Therefore, a Gaussian membership function is employed to fuzzify the image to obtain a smooth and differentiable fuzzy model [36].

However, the image is poor in contrast and has nonuniform illumination, thus applying a single Gaussian membership is not suitable to fuzzify the entire region in the image. Different membership functions must be applied accordingly to ensure that they can provide a perfect function to fuzzify the dark and bright regions in the image.

The Gaussian functions are modified to fuzzify dark (i.e., underexposed) and bright (overexposed) regions separately as derived in Eqs. (4) and (5).

$$\nu(X_u) = \left| X_{\max} - \exp\left[-\frac{(X_{\max} - (X_{avg} - X_u))^2}{\tau_h^2}\right] \right| \\ \text{for} \quad X < T \qquad (4)$$

$$\nu(X_o) = \left| \exp\left[-\frac{(X_{\max} - (X_{avg} - (L - X_o)))^2}{\tau_h^2}\right] - X_{\min} \right| \\ \text{for} \quad X \geq T \qquad (5)$$

where X_u indicates the gray levels in the underexposed region in the range $[0, T-1]$, X_o indicates the gray levels in the overexposed region in the range $[T, L-1]$ and τ_h^2 is the membership factor, calculated using Eq. (6):

$$\tau_h^2 = \alpha \left[\frac{\sum_{X=0}^{L-1}[(X_{\max} - \sigma_X) - X]^4 \, p(X)}{\sum_{X=0}^{L-1}[(X_{\max} - \sigma_X) - X]^2 \, p(X)}\right] \qquad (6)$$

where σ_X is the standard deviation of the original image. The α and $p(X)$ are the fuzzified factor and histogram of the gray levels, respectively. The membership function in Eq. (4) operates in the region below threshold T, whereas the membership function in Eq. (5) operates in the region above the threshold T.

The membership function is then modified according to its respective region to enhance the image once the image is converted into the fuzzy domain. Different functions will be used for enhancing both regions (i.e., dark and bright regions) as applied in the fuzzification process. The parametric sigmoid functions for enhancing the dark (underexposed) and bright (overexposed) regions are given

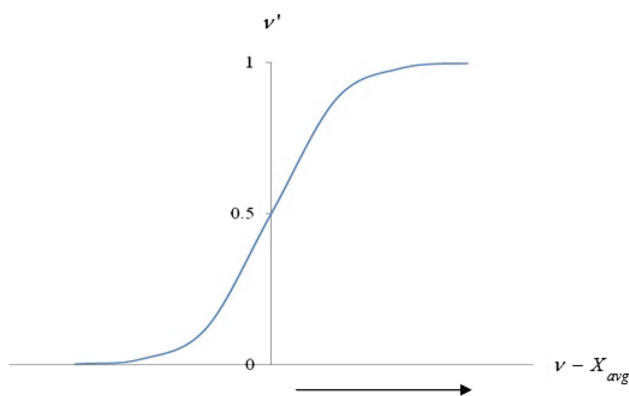**Fig. 2** Block diagram of fuzzy enhancement process
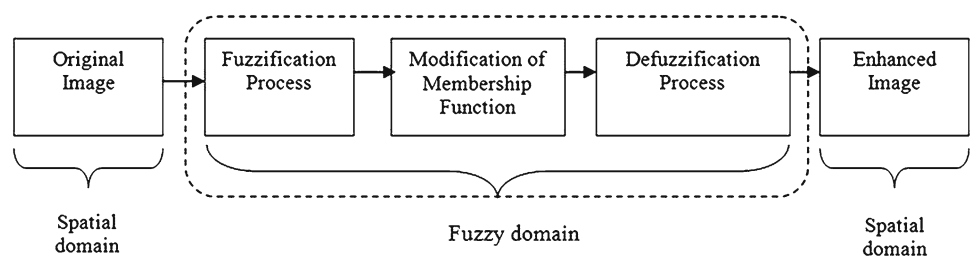
Fig. 3 Example of the sigmoid function

by Eqs. (7) and (8), respectively:

$$v\prime(X_u) = \frac{1}{1 + e^{-[-g(v(X_u) - X_{avg})]}} \qquad (7)$$

$$v\prime(X_o) = \frac{1}{1 + e^{-[-h(v(X_o) - X_{avg})]}} \qquad (8)$$

where g and h are the enhanced factors that are used to enhance the fuzzified image. The sigmoid function is chosen because it will achieve a value close to '1' if the exponential parameters presented in Eqs. (7) and (8) are approaching infinity (Fig. 3). Therefore, the unsaturated intensity of the fuzzified image is ensured by this sigmoid function. The aforementioned have modified the membership function and enhancing the original recorded image. Both regions are combined to produce an enhanced image once the fuzzified image is modified,

The modified membership functions are defuzzified using their respective inverse membership functions.

$$Y = \begin{array}{ll} v\prime_u^{-1}(X) & \forall X < T \\ v\prime_o^{-1}(X) & \forall X \geq T \end{array} \qquad (9)$$

The gray levels in the underexposed region are scaled back in the range between $[0, T-1]$, whereas the gray levels in the overexposed region are translated and scaled in the range between $[T : L-1]$. Both regions are then combined into a single region for enhancing the image. The flow chart of the complete enhancement process is illustrated in Fig. 4.

The proposed techniques can be also applied in color image enhancement. A proper color space model that can be used is Hue, Saturation and Intensity color model. This model decouples the chromatic information from the achromatic information. Color artifacts may be introduced if the enhancement is directly conducted in three color spaces of red, green and blue (RGB).

5 Results and discussions

The experimental results using of standard images obtained from the California Institute of Technology Computational Vision database [35] is presented in this section. We demonstrated the performance of the developed algorithm compared with other existing fuzzy gray-scale enhancement techniques.

The performances of the proposed method are compared with the other techniques that also implement the fuzzy theory in image enhancement for fair comparison. Five groups of fuzzy image enhancement techniques exist as discussed in Sect. 1. These techniques include the conventional approach of the (NINT) [1], the application of the fuzzy IF-THEN rules (FRB) [14], the fuzzy objective measure (FOM) [26], the fuzzy local enhancement (FL) [31] and the fuzzy histogram-based equalization technique (FHE) [13].
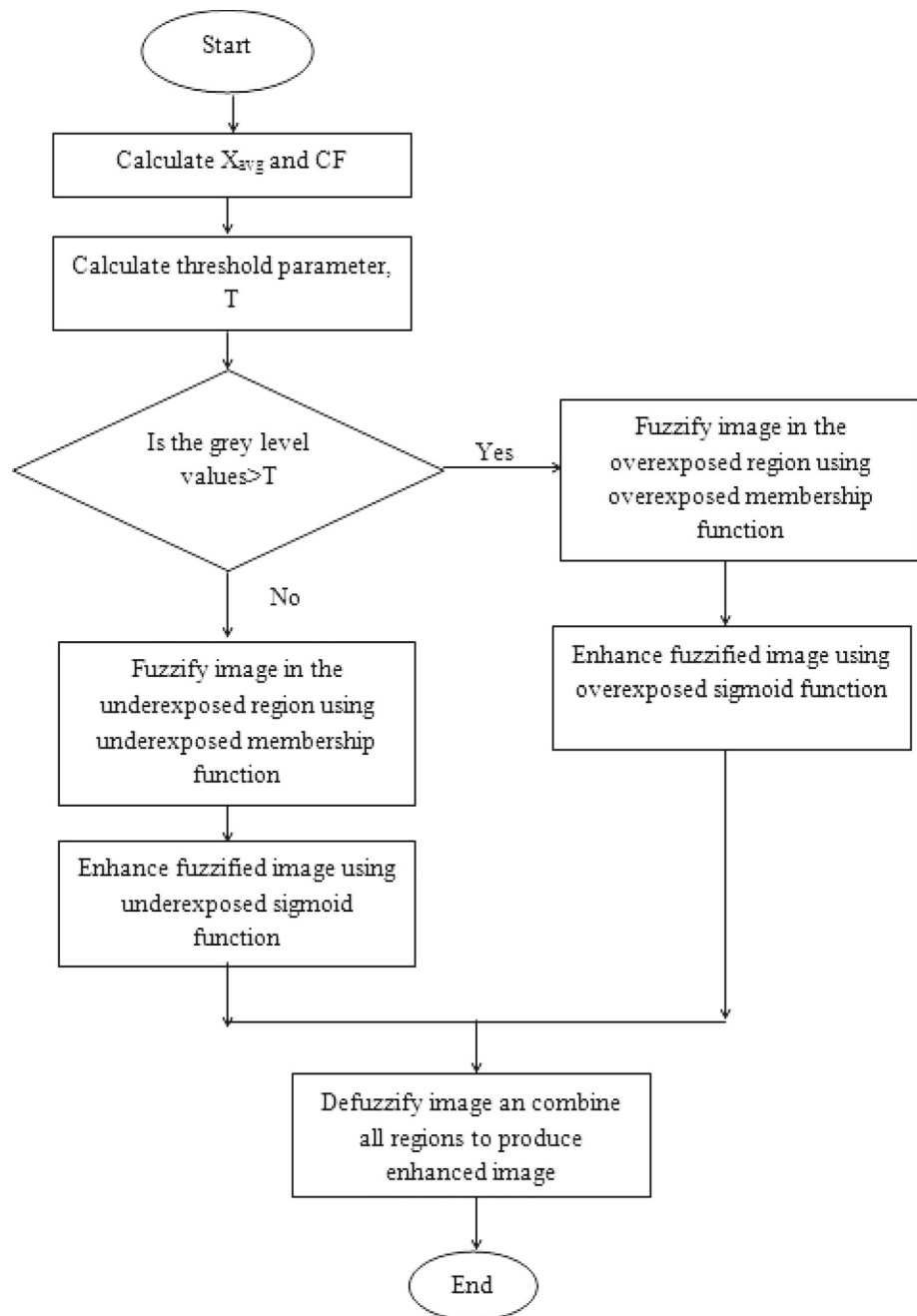
Even though the NINT [1] and the FOM [26] approaches enhanced the image in color model, both are worth consideration because only the gray levels are used without modifying the color components in the image. Hence, we selected these two methods in literature because both are similar approach with our technique, which only adjusts the gray levels to enhance the recorded image.

The FRB [14] and FL [31] methods are relevant compared with our proposed method because these techniques are related to our local contrast factor measurement. Both methods enhance the image by using the information contained in the local neighborhood which can be related to our approach. We also considered the histogram-based approach by choosing the FHE [13] method because it dealt with the crisp histogram of the images that considers the inexactness of the gray-level values to enhance contrast.

The experimental results are compared qualitatively and quantitatively with the aforementioned techniques. The goal of this study is to propose a new computationally fast enhancement technique. In addition, the luminance of the enhanced image is required to be as close to the original image as possible to preserve image brightness and details while suppressing noises. Enhancement is conducted based on global and local information to preserve the details and mean luminance of the image according to the aforementioned requirements. Qualitative analysis is performed by visual comparison, whereas the luminance distortion (LD), entropy (E), peak signal-to-noise ratio (PSNR) and processing time (t) are chosen for quantitative analysis.

LD is selected because it is proposed by a previous study [37] that considered the correlation of mean luminance between the enhanced and the original images. LD is given in Eq.(10).

Fig. 4 Flowchart of the complete enhancement process

$$LD = \frac{2\bar{X}(\bar{Y})}{(\bar{X})^2 + (\bar{Y})^2} \tag{10}$$

where

$$\bar{X} = \frac{1}{L} \sum_{i=1}^{L} x_i \tag{11}$$

$$\bar{Y} = \frac{1}{L} \sum_{i=1}^{L} y_i \tag{12}$$

X_i and Y_i are the gray-level values for the original and enhanced images, respectively. The LD is in the range [0 1]. The mean luminance of the enhanced image is almost similar to the original image if the LD approaching '1' which means that $\bar{X} \approx \bar{Y}$. Thus the brightness is preserved.

In addition to the brightness preservation, the details of the image also need to be maintained. Therefore, the entropy analysis is used to measure the capability of detail preservation. A higher entropy indicates the higher ability of the

(a)   **(b)** LD=0.989, E=6.745, PSNR=25.8311, t=0.177s   **(c)** LD=0.849, E=5.880, PSNR=12.550, t=0.1073s   **(d)** LD=0.942 E=5.730, PSNR=24.224, t=0.843s

(e) LD=0.988, E=6.881, PSNR=10.348, t=39.417s   **(f)** LD=0.992, E=7.601, PSNR=14.741, t=67.667s   **(g)** LD=0.982, E=7.233, PSNR=22.138, t=0.173s

Fig. 5 Comparison of enhancement results **a** original 'Lena' image, **b** proposed method, **c** NINT [1], **d** FOM [25], **e** FRB [13], **f** FL [30], **g** FHE [12]

proposed method to overcome intensity saturation problems and preserve more details of the image. The entropy of the enhanced image is given by:

$$E = \sum_{i=0}^{L-1} p(Y_i) \times \log_2 p(Y_i) \qquad (13)$$

where $p(Y_i)$ is the probability of enhanced gray levels Y_i

The enhancement technique should not significantly amplify the noise level. Thus PSNR analysis is employed. Good enhancement techniques should be able to increase image brightness without enhancing existing noises in the recorded image. The PSNR is calculated using Eq. (14).

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

$$\text{MSE} = \sqrt{\frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \left(Y_{i,j} - X_{i,j}\right)^2}{C \times R}} \qquad (15)$$

The last analysis is the processing time, which is used to measure the computational complexity introduced by the proposed method. For consistency, 100 standard images size 400×264 pixels are used for each method. The samples are processed in the Matlab R2010a environment using an Intel Core 2 CPU 2 GHz with 2.49 GB RAM.

The proposed method should produce the enhanced image with an LD is close to '1' and have a high entropy to ensure brightness and to preserve details. In addition, the enhanced image is expected to have a high PSNR value and can be executed with short computational time.

Several low contrast images which are actually underexposed were used for qualitative evaluation. These images are "Lena", "Room", and "Fruits", as shown, respectively in Figs. 5, 6, and 7. The figures show the enhanced images from the proposed approach compared with other existing state-of-the-art approaches. The enhanced images from the NINT [(Figs. 5c, 6c, 7c) and FOM (Figs. 5d, 6d, 7d)] approaches have resulted in darker images compared with the original images. Image contrast is decreased. Thus, distinguishing the foreground from the background is difficult. The mean luminance of the enhanced images for both methods deviates from the mean luminance of the original image, thus resulting in lower LD values. The lower LD values indicate that those methods are unable to preserve the mean brightness of the original image.

In terms of detail preservation, the entropy values of the enhanced image using the NINT approach in Figs. 5, 6, and 7 are 5.880, 4.673, and 4.327, respectively. The NINT approach produced the lowest entropy value compared with the other methods. Most of the areas in the enhanced image
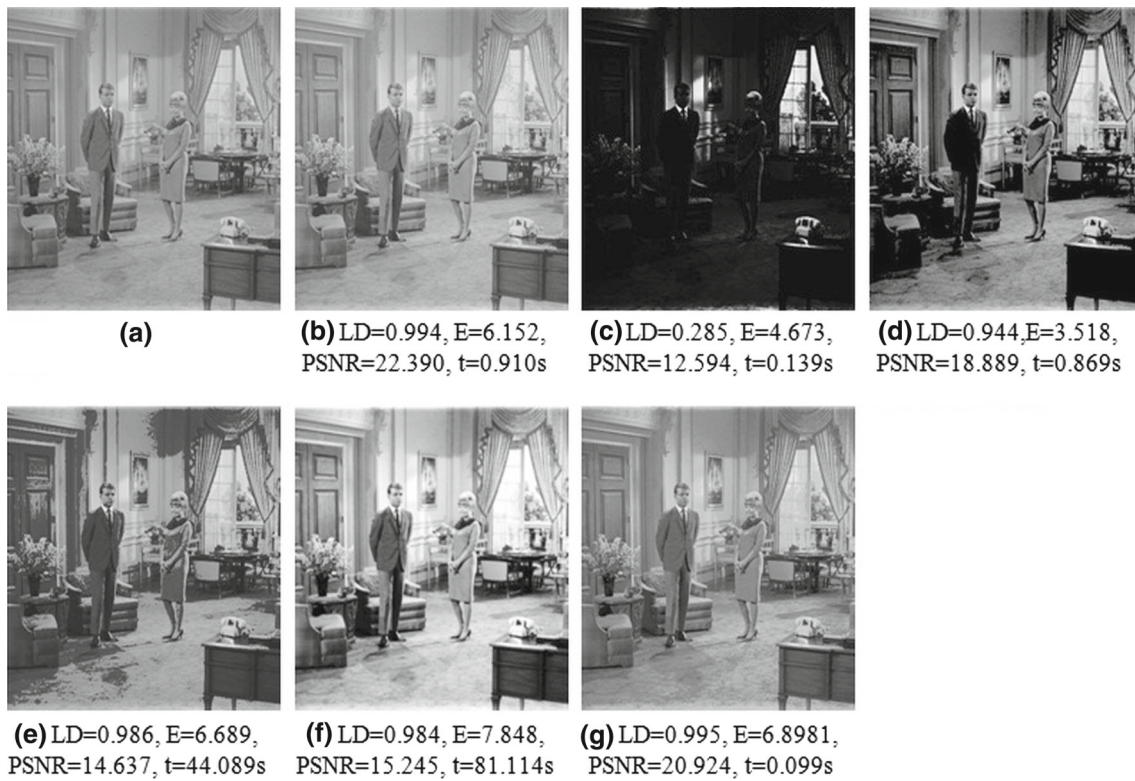
(a)

(b) LD=0.994, E=6.152, PSNR=22.390, t=0.910s

(c) LD=0.285, E=4.673, PSNR=12.594, t=0.139s

(d) LD=0.944, E=3.518, PSNR=18.889, t=0.869s

(e) LD=0.986, E=6.689, PSNR=14.637, t=44.089s

(f) LD=0.984, E=7.848, PSNR=15.245, t=81.114s

(g) LD=0.995, E=6.8981, PSNR=20.924, t=0.099s

Fig. 6 Comparison of enhancement results **a** original 'room' image, **b** proposed method, **c** NINT [1], **d** FOM [25], **e** FRB [13], **f** FL [30], **g** FHE [12]
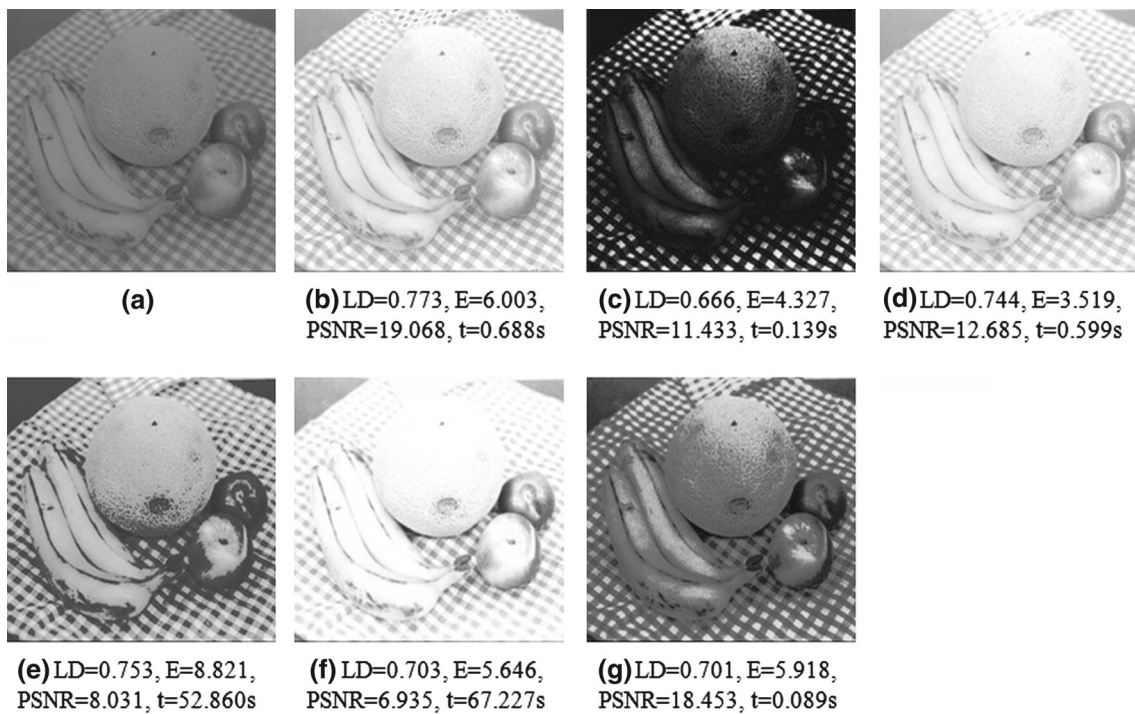

(a)

(b) LD=0.773, E=6.003, PSNR=19.068, t=0.688s

(c) LD=0.666, E=4.327, PSNR=11.433, t=0.139s

(d) LD=0.744, E=3.519, PSNR=12.685, t=0.599s

(e) LD=0.753, E=8.821, PSNR=8.031, t=52.860s

(f) LD=0.703, E=5.646, PSNR=6.935, t=67.227s

(g) LD=0.701, E=5.918, PSNR=18.453, t=0.089s

Fig. 7 Comparison of enhancement results **a** original 'fruits' image, **b** proposed method, **c** NINT [1], **d** FOM [25], **e** FRB [13], **f** FL [30], **g** FHE [12]

Fig. 8 Comparison of enhancement results **a** original 'Man 1' image, **b** proposed method, **c** NINT [1], **d** FOM [25], **e** FRB [13], **f** FL [30], **g** FHE [12]

appear dark, with poor brightness. As such, the details of the image are not apparent and cannot be interpreted by the eyes. The NINT technique underenhanced certain regions because the underexposed and overexposed regions of the image were not considered during processing. The NINT technique enhances the image without preserving the details and contrast of the original image. The algorithm also enhances existing noise in the original image, resulting in a lower PSNR value.

The less-enhanced and slightly saturated images are produced through the FRB method, as shown in Figs. 5e, 6e, 7e with PSNR values of 10.348, 14.637, and 8.031, respectively. Conversely, the proposed method enhanced the image while preserving brightness as shown by the highest LD value. The proposed method did not enhance existing noise, as indicated by the highest PSNR value among the different methods.

Figures 5, 6, 7 also show how the FL method overenhanced the original images, resulting in brighter and unnatural images. Our proposed method can be executed quite fast, while preserving details and brightness.

The proposed method is analyzed using mixed-type images to demonstrate its effectiveness in image enhancement. A mixed-type image consists of underexposed (mostly at the image background) and overexposed (mostly at the image foreground) regions in a single image, as shown in

Figs. 8a, 9a, 10a, 11a, and 12a. Our goal is to enhance the image without overenhancing the overexposed region or underenhancing the underexposed region or both. Thus, Figs. 8, 9, 10, 11, 12 are compared with other state-of-the-art methods.

These figures show that the NINT and FOM techniques underenhanced the original image and caused the processed images to look darker than the original image. Both methods enhanced the foreground while producing a darker background. As a result, the enhanced images exhibit improved contrast than the original image, which is also reflected in their respective entropy values. However, both techniques fail to maintain the mean brightness of the original image. Thus, the enhanced images are unpleasant and unnatural to look at. Both methods produced darker images, thus information and details in the images were reduced.

Figures 8, 9, 10, 11, 12 show that the improvement attained with the proposed technique results in a more pleasing enhanced image compared with those produced using the other techniques. The FRB and FL methods overenhanced certain regions (foreground area) of the image because the whole image was enhanced, but the underexposed and overexposed regions of the image were not considered. In addition, the FRB method caused intensity saturation at certain regions of the image, resulting in additional noises caused
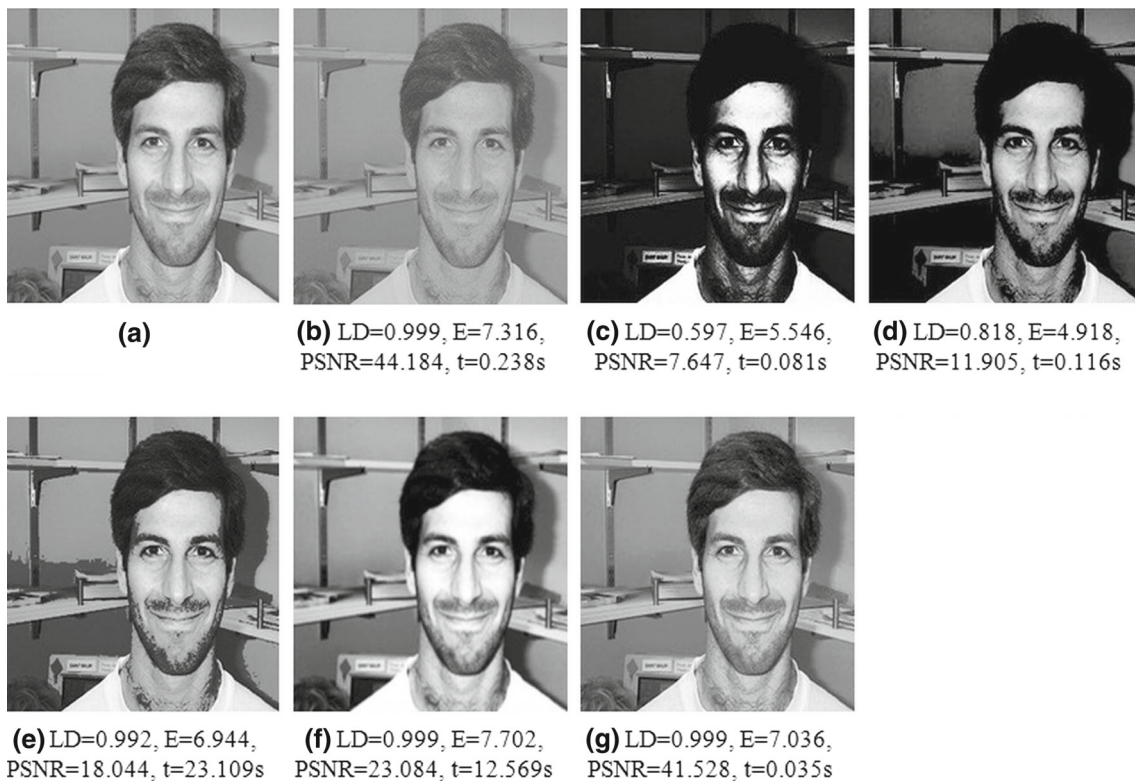
Fig. 9 Comparison of enhancement results **a** original 'Man 2' image, **b** proposed method, **c** NINT [1], **d** FOM [25], **e** FRB [13], **f** FL [30], **g** FHE [12]

Fig. 10 Comparison of enhancement results **a** original 'Woman 1' image, **b** proposed method, **c** NINT [1], **d** FOM [25], **e** FRB [13], **f** FL [30], **g** FHE [12]
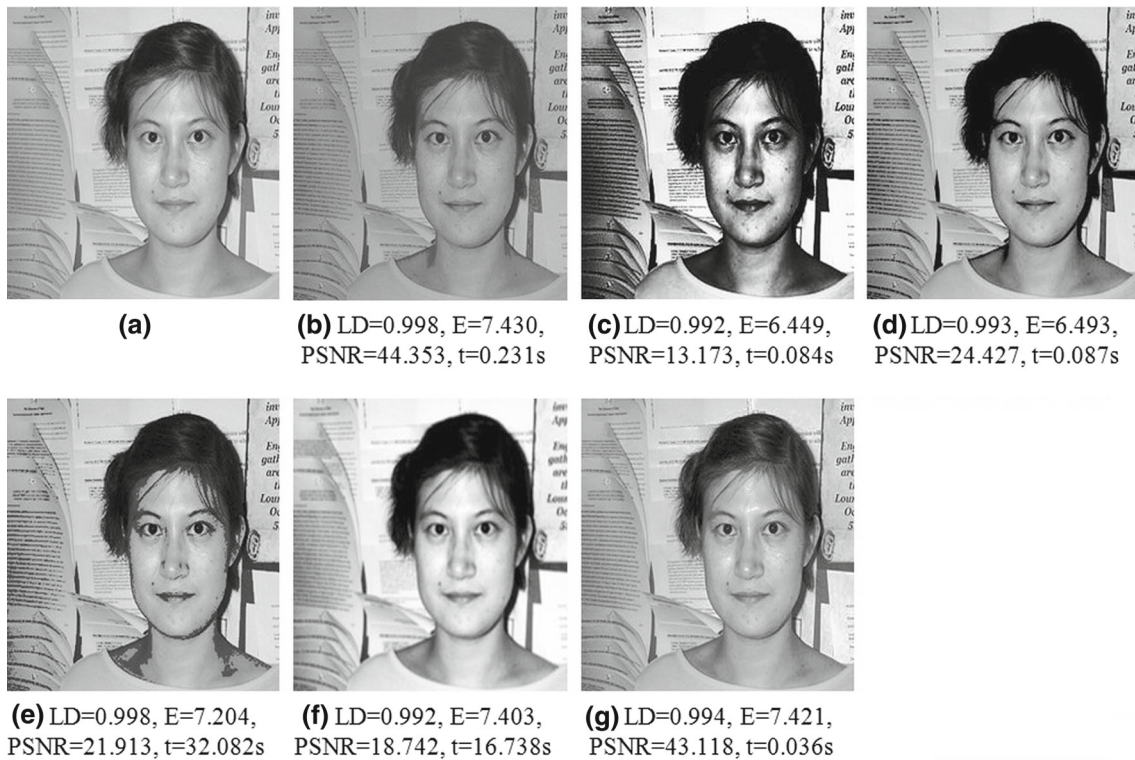
Fig. 11 Comparison of enhancement results **a** original 'Woman 2' image, **b** proposed method, **c** NINT [1], **d** FOM [25], **e** FRB [13], **f** FL [30], **g** FHE [12]
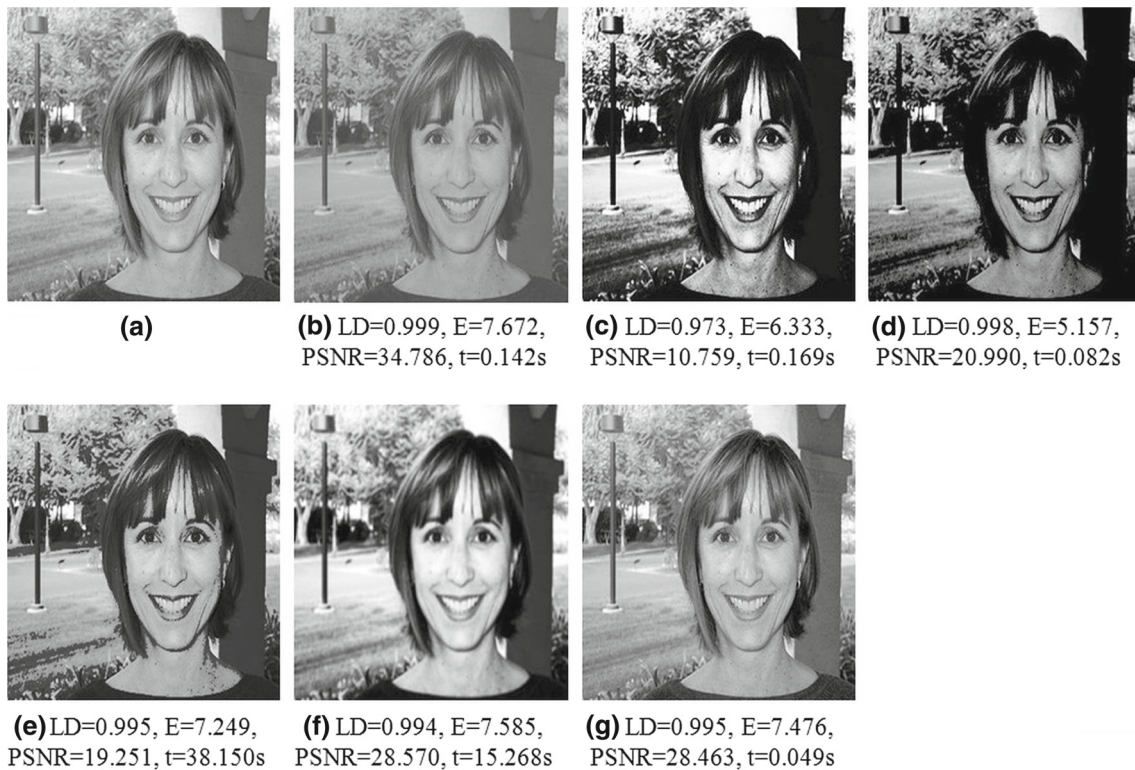

Fig. 12 Comparison of enhancement results **a** original 'Woman 3' image, **b** proposed method, **c** NINT [1], **d** FOM [25], **e** FRB [13], **f** FL [30], **g** FHE [12]

Table 1 Comparison of average quantitative analysis for 100 images

Techniques	$t(s)$	PSNR	E	LD
Proposed method	0.181	**39.543**	**7.560**	**0.999**
NINT [1]	0.149	14.170	6.027	0.918
FQM [25]	0.146	17.13	4.778	0.868
FRB [13]	22.169	21.843	7.134	0.99
FL [30]	16.055	19.065	7.472	0.997
FHE [12]	**0.035**	37.971	7.330	0.991

by unnecessary saturation. This condition is also reflected in the low PSNR values of the images.

The proposed technique is faster to execute and produces a more pleasing image compared with the FRB and FL methods. This result happened because brightness was improved accordingly with their respective regions (underexposed and overexposed regions). The intensity in the underexposed regions was increased using a modified sigmoid function in the proposed approach, as presented in Eq. (7). By contrast, the intensity in the overexposed regions was decreased by the respective sigmoid function derived in Eq. (7). Therefore, the dynamic range of the enhanced image is obtained, and the mean luminance or brightness is preserved. The sigmoid functions have avoided the intensity saturation problem, as discussed in the previous section.

The resulting image from FHE approach has an overenhanced foreground, thus causing intensity saturation in certain images as shown in Figs. 10g and 11g. Although the FHE approach is computationally fast, our proposed method produces an enhanced image with better quality, as shown by the quantitative values of LD, E, and PSNR.

The results of the quantitative analysis are given in Table 1, wherein comparison is conducted based on the average values of processing time, PSNR, LD, and E obtained from simulating 100 standard images. The best results obtained for each analysis are presented in bold text. Table 1 indicates that the proposed method gives the best performance, in terms of the highest PSNR, and by exhibiting an LD close to '1'. Therefore, the proposed method is better in preserving brightness. The entropy of the enhanced image resulting from the proposed method also defeated those of other techniques, thus indicating better contrast and detail preservation. However, in terms of processing time, FHE is the fastest to be executed because the image is treated as a mixed region in which overexposed and underexposed regions are not considered.

6 Conclusions

A new fuzzy enhancement technique is proposed for degraded gray-scale images. The new enhancement approach considers poor contrast and nonuniform illumination problems that often occur in a recorded image. A new parameter, called the contrast factor, is proposed based on differences in the gray-level values of pixels in the local neighborhood. Improved image quality is obtained, and the proposed method is able to preserve the details and the mean luminance of the image. The proposed method defeats other methods in terms of LD, detail preservation, and noise suppression. The proposed algorithm has a comparably fast processing time of approximately 181 ms. Thus, the proposed algorithm is a suitable approach for real-time applications.

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