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MODIFIED FAST GRAY LEVEL GROUPING APPROACH FOR ENHANCING IMAGE CONTRAST

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ABSTRACT

Images with low contrast may have intensity properties that make it difficult to use the traditional algorithms and approaches to enhance its contrast. Image's histogram may contain high frequency values in specific area in the image and low frequency in the remaining area. That leads to inconsistency in the histogram and results in image with unacceptable contrast. Two algorithms are proposed to solve this problem, namely MFGLG and ACEIF/MFGLG approaches. The first approach is Modified Fast Gray Level Grouping (MFGLG). It is a modification of Fast Gray Level Grouping (FGLG). MFGLG uses two sets of gray level bins and uses them as a startup bins assigned to the histogram. The proposed approach results in more efficient contrast enhancement compared to FGLG. The algorithm has no user intervention. Moreover, the proposed algorithm can be applied to vast range of contrast perturbed images. It also can be applied to images with the highest frequency in the histogram concentrated in any image location. The second approach is Automatic Contrast Enhancement Image Fusion based on Modified Fast Gray Level Grouping (ACEIF/MFGLG). With ACEIF/MFGLG, the output of MFGLG is fused with the original image to get more detailed image. The original image is used to provide more accurate contrast and intensity. The proposed two approaches are applied on low-contrast images and provides high quality images. The algorithm can be applied without human intervention with acceptable speed compared to the other methods in literature.

Keywords: *Image Fusion, Histogram, Contrast Enhancement, Image Enhancement.*

1. INTRODUCTION

image improve and enhancement is vast branch in image processing and handling. Image enhancement principle target is to improve the nature of the picture and raise its quality. The improvement strategies can be found in spatial or frequency domains [1]. Examples of image enhancement techniques are, image filtering, histogram equalization, and contrast enhancement, refer to Figure 1. In this paper we focus our research on contrast enhancement in spatial domain [2]. Contrast enhancement is widely used algorithm for improving the low contrast image visual quality. Generally, poor contrast in which an image may lose detailed information such as sharp edges and distinct patterns, may introduce effects such as wash-out and blurring. Contrast enhancement focuses on dynamic range of the image and introduce solutions for improving it. Contrast enhancement techniques are divided into direct and indirect algorithms. Direct algorithms find a specific contrast measure and try to improve it. Meanwhile, indirect methods focus on the under-utilized areas of low contrast image and improve the dynamic range of these areas. Most contrast enhancement methods fall into an indirect group. The indirect methods are decomposed into the following steps:

- Image decomposition, in which the image is decomposed into low and high frequency components for further analysis.
- Histogram modification. The intensities are changed by modifying the image's histogram. Histogram Equalization (HE) is widely used technique for image enhancement.

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- Transformation: the image is transformed into another domain for easier manipulation

The most important step here is the Histogram Modification, namely Histogram Equalization. Histogram Equalization obtained attention in image enhancement research due to its simplicity in implementation in addition to the visual quality results it introduces [5]. HE changes the distribution of the histogram. It utilizes frequent pixel intensities and spreads them out on all other intensities. In addition, the less frequent pixel values are exaggerated to have equal chance of being in all intensity values. The resulting distribution is approximately uniform distribution [3]. However, HE has a problem of changing the image brightness, especially in low-contrast images. A wide range of images may have histogram with high amplitude concentrated in the first component of the Nonzero histogram component (NZHC) and low amplitude for the remaining image intensity. This type of images may include visual artifacts such as washing-out and added-noise when processed with HE [4].

In general, traditional contrast enhancement techniques are application dependent. When the image is processed for contrast enhancement, the suitable processing parameters are selected and fine-tuned until a satisfactory result is met. Traditional contrast enhancement algorithms are not applied automatically on the image. Instead, it needs user intervention to adjust parameters to reach the expected results. Therefore, a wide range of images can't be ideally processed with traditional methods automatically. Especially the images with histogram having very large amplitude for specific gray-scale intensities. While having very small amplitude not reaching zero in the remaining gray-scale values. The mentioned Histogram type with high-low variations makes it difficult to adjust the brightness of the images by simply stretching out intensity values. If the stretching is done automatically for such type of histograms, washing-out and image noise magnification artifacts maybe faced in the processed image [6]. If the high amplitude in the histogram is corresponding to the image background, it will lead to the amplification of the background image noise.

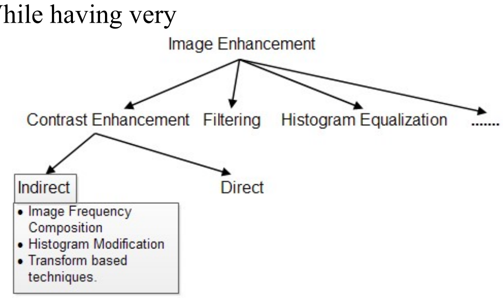

Fig.1. Classification of image enhancement techniques. The proposed research is focused on indirect contrast enhancement techniques.

In this paper, two approaches for automatic contrast enhancement have been proposed. The research of the paper is focused on the images with histogram that contain amplitude component with high values at one location and small values at other location. The first proposed approach is Modified Fast Gray Level Grouping (MFGLG) which is an enhancement of the traditional Fast Group Level Grouping (FGLG) technique. The second approach is Automatic Contrast Enhancement Image Fusion based on modified Fast Gray Level Grouping technique (ACEIF/MFGLG). With ACEIF/MFGLG there are three image processing phases. The first phase is a preprocessing phase in which filters are applied on the source image. The second phase is to apply filters on the MFGLG enhanced image. Finally, the third phase is to apply image fusion technique [7] to combine the source and the enhanced image to form new fused image with more detail and higher contrasted visual quality. The rest of the paper is organized as follows; in section 2 the related work is explored. In section 3 The proposed two approached are presented in detail. In section 4 The results and discussion together with experimental analysis are proposed. Finally, the conclusion and future trends are presented in section 5.

2. PREVIOUS APPROACHES

Previous research has been focused on improving image contrast by using histogram equalization techniques. In [8] authors proposed a mean preserving bihistogram equalization technique (BBHE). In BBHE, the main objective is to eliminate the brightness preservation problem. This is done through dividing the image histogram into two parts using the input mean. The equalization is applied on both parts separately. Another equal area histogram-based technique called Dualistic Sub-Image Histogram Equalization (DSIHE) is proposed in [9].

In DSIHE the main objective is to maximize the image entropy by dividing the input image into two images. The division separator is the image median. In addition, a histogram-based contrast enhancement technique called Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) is proposed in [10], [11]. MMBEBHE is an enhancement of the previously proposed BBHE approach. MMBEBHE successfully maximized the brightness preservation compared to BBHE. Even though the proposed algorithms introduced better contrast enhancement, they introduce visual artifacts and annoying effects. The artifacts or the annoying effects may be reduced for only specific histogram distributions. If there are high variations of the gray levels intensities in the histogram, the mentioned algorithms will introduce low performance in image contrast adjustment [12]. Another important improvement for BBHE is Recursive Mean-Square Histogram Equalization (RMSEHE) [10]. However, researchers in [13] proved that it also introduced visual artifacts with various types of histogram distributions.

Most of mean brightness preserving histogram equalization (MBPHE) methods [25] lies behind two broad groups. The first group is bisection MBPHE. Bi-section MBPHE is the basic group because of its simple and straight forward implementation. The second group is multi-section MBPHE. The main approach in both groups is to divide the histogram into two sections. The histogram equalization is then applied on both sections separately. The main difference between MBPHE approaches is the criteria used to divide the image histogram [8]. A more powerful technique called Dynamic Histogram Equalization (DHE) outperformed the state of the art traditional HE algorithms. It enhances the image without losing any image detail. Its strength came from its ability to divide the histogram according to histogram's local minima. It then adaptively assigns gray level ranges for each division before applying the histogram equalization. The partitioning process is repeated recursively to make sure that there is no dominant partitions. DHE method introduced higher performance compared to present approaches by increasing the contrast quality of the equalized image and remove undesirable washing out and checkboard effects [13].

An extension of HE is the Brightness Preserving Dynamic Histogram Equalization (BPDHE) [14]. BPDHE equalizes the image with keeping the mean intensity approximately equal to the mean intensity of the original image. BPDHE is referred to as mean intensity preserving approach.

Four techniques can be combined to produce novel approach that enhances local and global image contrast and introduces minimal distortion. For example, in [14] BPBHE technique, Multiple grapy level thresholding, Global histogram equalization and Connected components analysis are combined to produce the Multilevel Component-Based Histogram Equalization approach (MCBHE). The approach Weighted Mean-Separated Sub-Histogram Equalization (WMSHE) [15] introduced an effective and enhanced contrast enhancement of the digital image. The Gray-Level Grouping method is introduced by Chen et. al [6] to enhance image contrast. This method facilitates an automatic choice of a histogram distribution to optimize contrast by using the maximum average distance between image's gray level pixels. The basic idea behind GLG is to partition the histogram of the low contrast image into groups according to a predefined criterion. The groups are then uniformly distributed on the remaining groups, so each group occupy approximately the same number of gray scales compared to its peer groups. Then the grouped components are ungrouped to the previous gray scale levels. Although GLG achieved the asserted effects in several cases, such as dark and low contrast images with a high histogram component on the leftmost side, it failed in cases with a high histogram component on the rightmost side or between grayscales. The problem is still related to the spacing between histogram components.

The basic GLG is providing a backbone for more advanced algorithms such as Fast Gray-Level Grouping (FGLG). In addition to Selective Gray-Level Grouping (SGLG) which start the histogram equalization with preprocessing steps. The preprocessing steps contain eliminating image noise and histogram enhancements. SGLG also has improved technique for dealing with colored images called Adaptive Gray-Level Grouping (AGLG) [16].

3. THE PROPOSED METHODOLOGY

A. Modified Fast Gray Level Grouping algorithm

The basic procedure of GLG [6] is to group histogram components of the low contrast image into a predefined set of groups. The grouping is done according to a predefined criterion. The histogram components for each group is redistributed uniformly on all gray scales. As a result, all groups have similar set of grayscales. The final step is to ungroup the previously grouped components to obtain the original enhanced histogram. GLG is a powerful algorithm applied on a vast majority of low contrast images and gives a reasonable result compared to traditional contrast enhancement technique. However, basic GLG still needs enhancements as it is not applicable to specific image types and give unexpected results with such type of images.

An improvement in the time complexity of GLG is introduced in Fast Gray-Level Grouping (FGLG), in fact, it is faster than basic GLG. The time is reduced by eliminating the need of iterations due to the need of applying transformation function and calculating for each group of bins the average distance between pixels. Instead of calculating the total number of gray level bins, it is predefined to be 20. FGLG has similar results compared to the basic GLG. It has also similar shortcomings as it only improves the images with histogram having highest amplitude component P_{hist} located in the left component of the nonzero components; None Zero Histogram Component (NZHC). These techniques can't help in enhancing contrast for images with the highest amplitude histogram component P_{hist} located in the right region on NZHC. Or the histogram has high amplitude component exist within the histogram [16].

The components in the left side of a grayscale histogram which maps the images' rear structure are mapped to a wider grayscale range [0, 170]. While the right components in the histogram are mapped to a narrower range [171,255].

Unlike FGLG, The proposed Modified Fast Gray-Level Grouping uses two groups of gray level bins as the default number of gray level bins. Our motivation in MFGLG method was to overcome the drawbacks for the basic GLG and FGLG techniques and improve their performance. The proposed MFGLG method achieves better results than FGLG method using a qualitative analysis depending on the human visual system and also quantitative analysis by suing quality measures such as Entropy, Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) [18], Structural Similarity Index (SSIM) [20] and Universal Image Quality Index (UIQI) [19] for the used images. It is also fully automated without user interaction. The proposed algorithm also has high speed performance. It is applied on standard images and process it in a couple of seconds on a standard personal computer. Moreover, it overcomes the drawback of the basic GLG as it can be applied to a broad category of images such as the images with the highest histogram component P_{hist} located at any location in grayscale.

The proposed MFGLG approach

Step 1: Suppose $H_n(k)$ represents the original image's histogram in which k represents the gray scale value in the range $[0,L-1]$. In this step, a gray level grouping is done by assigning the nonzero histogram components to the gray level groups. The groups are denoted by $Gn(i)$:

$$G_n(i) = H_n(k), for H_n(k)\ 6{=}\ 0, \quad k = 0,1,\ldots,L-1; i = 1,2,\ldots,n \qquad (1)$$

Step 2: The gray level intervals for each group has left and right intervals, $L_n(i)$ and $R_n(i)$, these limits are saved.

$$L_n(i) = R_n(i) = k, for H_n(k)\ 6{=}\ 0, \quad k = 0,1,\ldots,L-1; i = 1,2,\ldots,n \qquad (2)$$

Step 3: Search for the group with the smallest amplitude and record its index i_{min}:

$$imin{=}argmini{=}1,2,\ldots,nGn(i) \qquad (3)$$

Step 4: The grouping is executed by combining the group having the smallest index $G_n(i_{min})$ with its adjacent small groups. The gray level bins $G_n(i)$ are manipulated to obtain new gray level bins $G_{n-1}(i)$:

$$G_{n-1}(i) = \begin{cases} G_n(i), & i = 1,2,\ldots,i'-1 \\ G_n(i_{min}) + G_{min}, & i = i' \\ G_n(i+1), & i = i'+1, i = i'+2, \ldots, n-1 \end{cases} \qquad (4)$$

$G_{min} = min\{G_n(i_{min}-1), G_n(i_{min}+1)\}$ And

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$$i' = \begin{cases} i_{min} - 1, & G_n(i_{min} - 1) \le G_n(i_{min} + 1) \\ i_{min}, & otherwise \end{cases} \quad (5)$$

Then the left and right side margins of the gray-level range related to $G_{n-1}(i)$ should be adjusted accordingly:

$$L_{n-1}(i) = \begin{cases} L_n(i), & i = 1, 2, ..., i' \\ L_n(i+1), & i = i' + 1, i = i' + 2, ..., n - 1 \end{cases} \quad (6)$$

And

$$R_{n-1}(i) = \begin{cases} R_n(i), & i = 1, 2, ..., i' - 1 \\ R_n(i+1), & i = i', i' + 1, ..., n - 1 \end{cases} \quad (7)$$

Step 5: If n-1=2, then go to step 6, else iterate step 3, in addition step 4.

Step 6: Build a transformation function $T_2(k)$, to map every gray value to its desired value. The range of gray levels are firstly estimated, in which every group will inhabit in image resultant as next;

$$N_{n-1} = \begin{cases} \dfrac{L-1}{n-1} & if\, L_{n-1}(1) \ne R_{n-1}(1) \\ \dfrac{L-1}{n-1-\alpha} & if\, L_{n-1}(1) = R_{n-1}(1) \end{cases} \quad (8)$$

Such that $\alpha = 0.8$ that be carefully chosen for numerous trails, $n - 1 = 2$. For each gray-level $k = 0, 1, L{-}1$ the transformed value $T_{n-1}(k)$ is identified based on the next four stages;

(1) When k belongs to group $G_{n-1}(i)$ and $L_{n-1}(i)$ =6 $R_{n-1}(i)$, then

$$T_{n-1}(k) = \begin{cases} N_{n-1}\left(i - \dfrac{R_{n-1}(i) - k}{R_{n-1}(i) - L_{n-1}(i)}\right) + 1 & if\, L_{n-1}(1) \ne R_{n-1}(1) \\ N_{n-1}\left(i - \alpha\dfrac{R_{n-1}(i) - k}{R_{n-1}(i) - L_{n-1}(i)}\right) & otherwise \end{cases} \quad (9)$$

(2) When k in groups $G_{n-1}(i)$ and $G_{n-1}(i +$

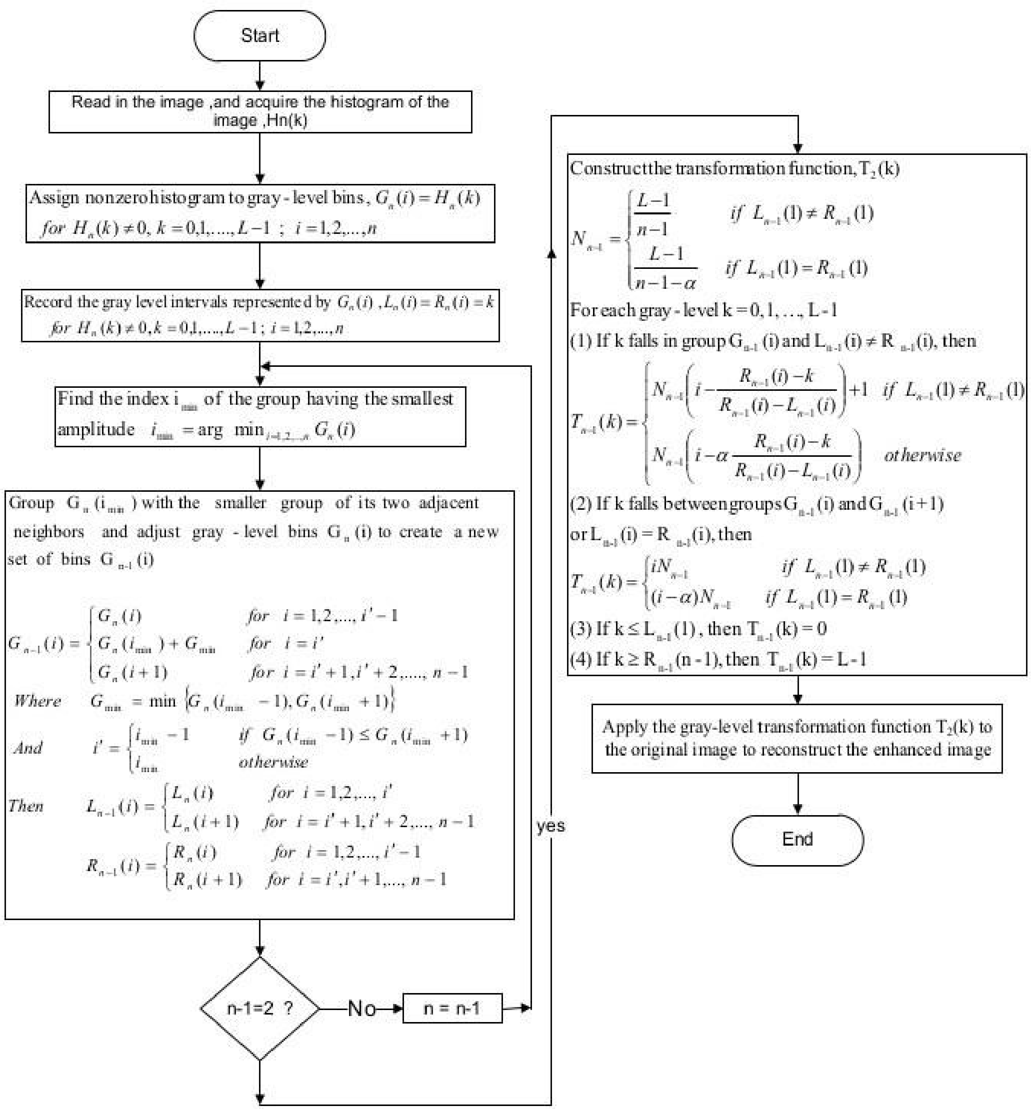

Fig.2. The Algorithm Of Our Proposed MFGLG Procedure.

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1) or $L_{n-1}(i) = R_{n-1}(i)$ then;

$$T_{n-1}(k) = \begin{cases} iN_{n-1} & if L_{n-1}(1) \neq R_{n-1}(1) \\ (i-\alpha)N_{n-1} & if L_{n-1}(1) = R_{n-1}(1) \end{cases} \quad (10)$$

(3) When $k \le L_{n-1}(1)$, then

$$T_{n-1}(k) = 0 \quad (11)$$

(4) When $k \ge R_{n-1}(n-1)$,then

$$T_{n-1}(k) = L - 1 \quad (12)$$

Step 7: Put on a gray-level transformation function $T_2(k)$ to an original image to rebuild the enhanced image.

The flowchart of our proposed MFGLG procedure is illustrated in Figure 2

B. Automatic Contrast Enhancement

The construct is automatically enhanced relied on Modified Fast Gray Level Grouping (ACEIF/MFGLG). It is being noted that the information of original image is generally revealed after applying the proposed MFGLG procedure. Motivating sufficient, the details that revealed in an original image as well as in MFGLG enhanced image are one of the complementary property. For this observation, the key idea is motivated to wrath an original image, in addition to its MFGLG enhanced image. Consequently, more details, visual quality and better contrast can be gained in the fused image using the second proposed ACEIF/MFGLG algorithm. In ACEIF/MFGLG algorithm, an automatic image fusion algorithm [22], [7] is used to combine the MFGLG enhanced image with the original source image. This algorithm assigns weight automatically, whereas other algorithms assign it manually [23].

The proposed ACEIF/MFGLG algorithm consists of three processes;

1. Image filtering as a pre-processing enhancement step for the source imageI_1 and the MFGLG output image I_2.
2. Calculation of the magnitude gradient for the source image I_1 and the MFGLG output image I_2.
3. Automatic calculation of image fusion weight (W), $0 \le W \le 1$ and using the nest equation to obtain an output fused image IF_{image} with respect to two images I_1 and I_2;

$$IF = W \times I_1 + (1 - W) \times I_2 \quad (13)$$

Image Filtering Process

In many applications of image and signal processing, it is fundamental to smooth the highly noised signals while simultaneously saving the edge information . The furthermost routinely utilized smoothing approaches are averaging filter, linear filter and median filter. Here, the linear filter is to wash out the noisy signals and smooth sharp edges. Shortly., this process is carried out to the source image I_1 as well as MFGLG output image I_2.

Median Filtering

A median filter is to determine the median for input elements. For standard median filter application, the window size (*WS*) is odd number. It is motivated lengthwise for examined estimations of signal or image. For each location in window, the median of these parts with *WS* are evaluated and and written to the yield pixel, which situated at a similar position as focal element of that window. The assessed median at this procedure is purported running median. Along these lines the size of window is consistent, the quantity of outgoing components is similar to input components quantity. [24]. Here, the dimension of used filter mask must be odd, in which the size may be 3×3,5×5, or 7×7. In numerous cases minimum mask size is chosen. So, the mask size is assign with 3×3 for analyzing our proposed method.

Padding

At the point when the mask centroid moves near the border, at least one column of the mask will be situated outer the image plane. There are numerous approaches to did this condition. Padding is one such way to deal with include rows and columns of ”0” s. Padding is uncovered off toward the finish of procedure with the end goal that the size of original image is the equivalent of filtered image.

Magnitude of image gradient calculation

We applied this task to source image I_1 and the MFGLG output to output image I_2, respectively. Mathematically, an image can be expressed via

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two-dimensional function $I(x,y)$. Here, the gradient of I at (x,y) is identified as two-dimensional column vector.

$$\nabla I = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \dfrac{\partial I}{\partial x} \\ \dfrac{\partial I}{\partial y} \end{bmatrix} \quad (14)$$

For this work, we employ the gradient magnitude, which computed by the next formula;

$$|\nabla I| = \left[\left(\frac{\partial I}{\partial x}\right)^2 + \left(\frac{\partial I}{\partial y}\right)^2 \right]^{\frac{1}{2}} \quad (15)$$

where $|\nabla I|$ is to magnitude of $|\nabla I|$. $\frac{\partial I}{\partial x}$ represents the derivatives for two-dimensional function $f(x,y)$ in direction x while $\frac{\partial I}{\partial y}$ refers to the derivative in direction y.

Approximately, the digital image processing of $\frac{\partial I}{\partial x}$ and $\frac{\partial I}{\partial y}$ are illustrated in Figure 3

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

Fig.3. Filter mask of order 3 × 3.

The furthermost frequently used filter mask is of order 3×3 where it can be estimated using the following Equations [1];

$$G_x = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \quad (16)$$
$$G_y = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7) \quad (17)$$

In gradient direction, the magnitude of it provides the maximum rate of $I(x,y)$ in per unit distance, for more detail the reader can refer to [1]. This is a significant measure to detect edges in images

Automatic weight calculation of image fusion

In our proposed algorithm, we use pixel-based fusion of the source image and its MFGLG to automatically enhance it [22]. It is noted that the weights can be automatically assigned [21]. Shortly, to automatically estimate the weights, the edge strengths of source image and it's MFGLG enhanced image are estimated firstly. Then the weight function is to compute the weight values rely on the strength of edges. Here, the estimated weight value is carried pixel by pixel. Thus, the resultant of this process to grayscale images as next;

- Suppose that the input image is I_1 while the MFGLG enhanced image is I_2.
- Estimate the magnitude gradient of I_1 to obtain the edge map S_1.
- Estimate the magnitude gradient of I_2 to obtain the edge map S_2.
- Compute $S = S_1 – S_2$.
- Compute the absolute greatest value for matrix S.
- Normalize the matrix S with respect to an absolute maximum value.

Then iterate the next steps for every pixel location (x,y);

- Compute $W = \left(\frac{1}{1 + 10^{-S(x,y)}}\right)$.
- The above function is used to give weight for each pixel depending on the strength of the edges I_1 and I_2. In case $S_1(x,y) > S_2(x,y)$, hence $I_1(x,y)$ is the obtained high weight and $I_2(x,y)$ is the nominated lower weight. On the other hand if $S_1(x,y) < S_2(x,y)$, hence $I_1(x,y)$ is the nominated higher weight and so forth.
- Find the fused image IF(x, y) based on the value of W with respect to Equation 13.

Figure 4 explores the flowchart of our proposed ACEIF/MFGLG algorithm

4. EXPERIMENT SIMULATION AND RESULT ANALYSIS

Measuring image enhancement is difficult and importance task. Many objective measures were proposed to measure the enhancement techniques. Five measures are used to evaluate the proposed algorithms. Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), Universal Image Quality Index (UIQI) [19], Entropy [18], and Structural Similarity Index (SSIM) [20] . These metrics measures the quality of image by different aspects such as

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luminance, contrast. Both of objective and subjective assessments are used in order to evaluate the algorithms.

The dataset used are collection of standarized gray level images of size 256 × 256 to evaluate the accuracy and performance of our proposed approach compared to previous approaches. The computations were performed in mathematical package MATLAB 2008a the specification of the test station is Intel core I3-3340M processor and 4 GB RAM memory

A. Objective Assessment

The following measurments MSE, PSNR, Entropy, UIQI, and SSIM are used to measure the image quality. HE [1], Fast Gray Level Grouping FGLG [6] and contrast enhancement algorithm [17] are simulated with various images to demonstrate the accuracy of the our approach. The experimental findings are shown in the table and the corresponding figure 5 .

Figure 5 displays the output results taken from 10 standard gray-scale images with different intensity variation values such as low contrast, high contrast, low light and dark . High entropy indicates that the proposed algorithms are preserving image details. The lowest MSE and highest PSNR values indicate that the updated and improved image is closed to the source image. However, UIQI values are close to unity this indicate that the natural appearance is preserving. In addition, it shows that even with higher SSIM values, the image structure and contents are preserved and kept intact.

The average of the processing time for the 10 images, shown in Table 1, is 4.7685 seconds in MFGLG algorithm and 5.9239 seconds ACEIF/MFGLG algorithm

B. Subjective Assessment

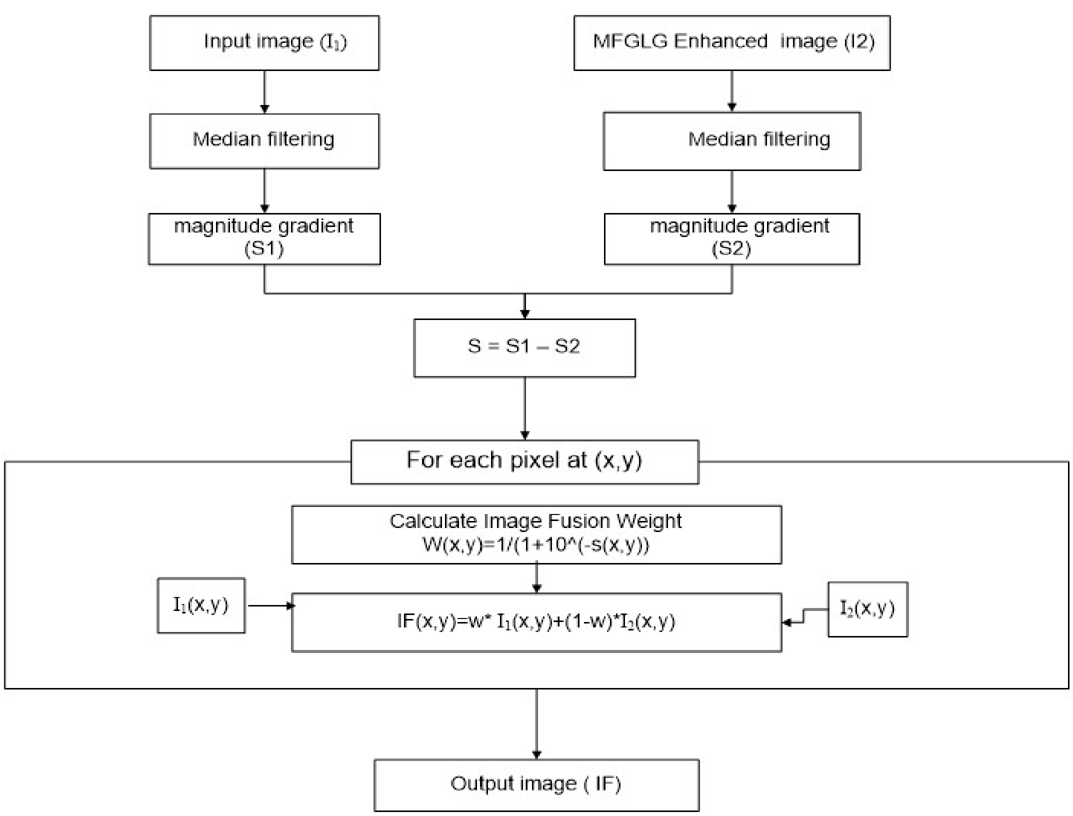

Fig.4. A Flowchart Of Our Proposed ACEIF/MFGLG Algorithm.

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Image	Quality measures	Original image	HE	FGLG	The Proposed MFGLG	Humied et al.	The proposed ACEIF/MFGLG algorithm
Lena	MSE	-	0.0122	0.0152	0.0020	0.0144	**6.1155e-004**
	PSNR	-	19.1239	18.1918	27.0596	18.4152	**32.1357**
	Entropy	7.4429	5.9735	6.9995	7.4429	6.2756	**7.5280**
	UIQI	-	0.8269	0.5649	0.9700	0.8269	**0.9901**
	SSIM	-	0.8573	0.5832	0.9723	0.8573	**0.9918**
pout	MSE	-	0.0469	0.0460	0.0389	0.0481	**0.0108**
	PSNR	-	13.2866	13.3708	14.1014	13.1786	**19.6715**
	Entropy	6.1875	5.7211	5.5907	6.1875	5.5250	**6.6231**
	UIQI	-	0.4516	0.4169	0.6640	0.4209	**0.8792**
	SSIM	-	0.5642	0.5303	0.7113	0.5356	**0.9223**
cameraman	MSE	-	0.0123	0.0127	1.4364e-004	0.0100	**4.3025e-005**
	PSNR	-	19.0970	18.9562	38.4273	20.0073	**43.6628**
	Entropy	7.0097	5.9106	6.3222	7.0097	6.3394	**7.0159**
	UIQI	-	0.6892	0.6503	0.9722	0.6611	**0.9939**
	SSIM	-	0.8069	0.7772	0.9705	0.7875	**0.9938**
Girl	MSE	-	0.0608	0.0499	1.5349e-005	0.0552	**3.8075e-006**
	PSNR	-	12.1593	13.0184	48.1392	12.5772	**54.1936**
	Entropy	7.2877	5.9549	6.6424	7.2877	6.6703	**7.2884**
	UIQI	-	0.6555	0.5765	0.9997	0.5378	**0.9999**
	SSIM		0.7211	0.6326	0.9997	0.5901	**0.9999**
einstein	MSE	-	0.0318	0.0342	0.0016	0.0365	**4.6506e-004**
	PSNR	-	14.9793	14.6553	28.0083	14.3734	**33.3249**
	Entropy	6.8936	5.9462	6.2634	6.8936	6.2197	**6.9313**
	UIQI	-	0.6250	0.5331	0.9914	0.5286	**0.9965**
	SSIM	-	0.6659	0.5661	0.9937	0.5609	**0.9979**
couple	MSE	-	0.0257	0.0309	1.5279e-005	0.0307	**3.7787e-006**
	PSNR	-	15.9077	15.1063	48.1589	15.1332	**54.2265**
	Entropy	7.1720	5.9594	6.5653	7.1715	6.2531	**7.1738**
	UIQI	-	0.6472	0.5095	0.9999	0.5300	**0.9999**
	SSIM	-	0.6753	0.5376	0.9999	0.5543	**0.9999**
boat	MSE	-	0.0216	0.0196	1.8264e-004	0.0257	**5.5154e-005**
	PSNR	-	16.6533	17.0861	37.3839	15.9064	**42.5842**
	Entropy	7.1583	5.9099	6.4983	7.1583	6.0018	**7.1708**
	UIQI	-	0.6286	0.5859	0.9963	0.5242	**0.9986**
	SSIM	-	0.6621	0.6152	0.9971	0.5446	**0.9992**
Stream and bridge	MSE	-	0.0129	0.0127	1.5300e-005	0.0137	**3.7814e-006**
	PSNR	-	18.8832	18.9462	48.1532	18.6226	**54.2235**
	Entropy	7.6682	5.9843	7.1977	7.6674	7.1737	**7.6673**
	UIQI	-	0.8518	0.7315	0.9999	0.7213	**0.9999**
	SSIM		0.8518	0.7253	0.9999	0.7150	**0.9999**
Moon	MSE	-	0.1150	0.0298	2.5646e-005	0.0265	**6.9065e-006**
	PSNR	-	9.3927	15.2613	45.9098	15.7610	**51.6074**
	Entropy	7.1583	4.2796	5.0836	5.4293	5.1070	**5.4357**
	UIQI	-	0.2322	0.2373	0.9712	0.2486	**0.9901**
	SSIM	-	0.2792	0.2815	0.9804	0.2927	**0.9942**
Airplane (F-16)	**MSE**	**-**	**0.0672**	**0.0775**	**0.0044**	**0.0678**	0.0012
	PSNR	**-**	**11.7268**	**11.1066**	**23.5705**	**11.6906**	29.0334
	Entropy	**6.7297**	**5.7377**	**5.7644**	**6.7296**	**5.6192**	6.8026
	UIQI	**-**	**0.4813**	**0.4585**	**0.9819**	**0.4886**	0.9907
	SSIM	**-**	**0.5617**	**0.5301**	**0.9894**	**0.5616**	0.9963

Fig.5. Comparison Results Of Different Algorithms With Proposed Algorithm.

Figure 6 to Fig 6 show the visual results of the implementation on three standard gray-scale images (pout, Einstein, Airplane (F-16)). The original image is poor in qaulity and contrast whenver the image objects are barely noticeable by bare eyes. Histogram Equalization has been used for improving the contrast of provided source image, but the details of the white region get over enhanced and the image worsens.

The Pout image has low contrast with overall high brightness as shown in Figure 6(a). Where the biggest amplitude values are located to the left of the histogram componenets P_{hist} = 84. The HE can't prevent the washed-out effect throug the entire images having significant variations in the image brightness as shown in Figure 6(b). The experimental results of the FGLG approach and contrast enhancement algorithm proposed by Humied et al. [17] as shown in Figures 6(c), Figure 6(e) show the overall brightness is still high with blurring so, its entropy is lower than the entropy of the

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original image. In the proposed MFGLG and ACEIF/MFGLG algorithms they preserve the image's natural appearance respectively and enhance the abrupt change in the image brightness as displayed in the Figure 6(d) and the Figure 6(f), respectively.

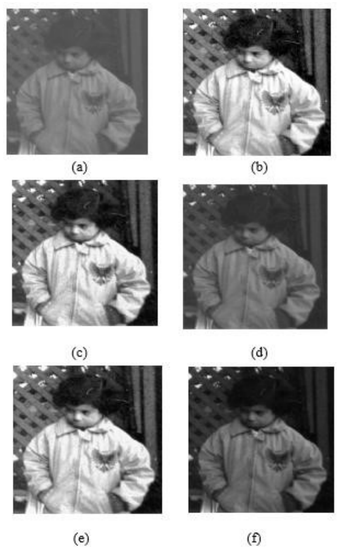

Fig.6. (A) Original 'Pout' Image ,(B) HE , (C) FGLG ,D) MFGLG ,(E) Humied Algorithm [17],(F) ACEIF/MFGLG Algorithm

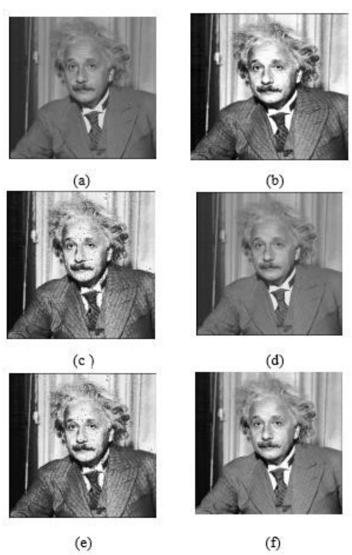

Fig.7. (A) Original 'Einstein' Image ,(B) HE , (C) FGLG ,D) MFGLG ,(E) Humied Algorithm [17],(F) ACEIF/MFGLG Algorithm

The Einstein image has the biggest amplitude values are located to the left of the histogram componenets, P_{hist}=111, as depicted in Figure 7(a). Figure 7(b) depicts the obtained result of HE with over enhancement. FGLG and contrast enhancement approach by Humied et al. [17] show that the noise has been increased and image details have been lost as depicted in Figure 7(c) and Figure 7(e), respectively. However, the results show that the proposed algorithms prevent the significant change in brightness and the washed-out appearance with preserving the naturalness of the image as shown in Figure 7(d) and Figure 7(f), respectively.

The Airplane (F-16) has the the biggest amplitude values are located to the right of the histogram componenets with P_{hist} = 212 and overall high brightness as shown in Figure 8(a). It has been observed that the washed-out appearance with dark background and significant change in brightness as results of HE and contrast enhancement algorithm [17] as shown in Figure 8(b) and Figure 8(e), respectively. The result of FGLG and contrast enhancement algorithm [17] shows that the image total brightness is still noticeably dark and the image details are blurred as shown in Figure 8(c). The result of the proposed algorithms Figure 8(d) and Figure 8(f) depicts that the images details are preserved, the over image enhancements are suppressed and the brightness change has been prevented.

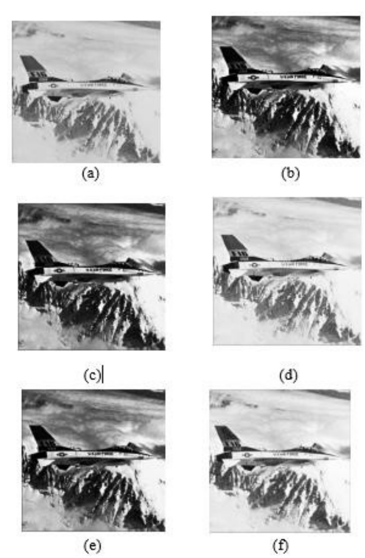

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Fig.8. (A) Original 'F-16' Image ,(B) HE , (C) FGLG ,D) MFGLG ,(E) Humied Algorithm [17],(F) ACEIF/MFGLG Algorithm

5. CONCLUSION

Automatic contrast enhancement techniques are presented in this paper. Modified Fast Gray Level Grouping (MFGLG) technique is proposed, based on Fast
Gray Level Grouping (FGLG) technique. In addition, an automatic contrast enhancement image fusion technique based on MFGLG is proposed. It used an automatic image fusion algorithm to combine the MFGLG output image with the original image. The main advantage of this technique is to integrate details from the original image with MFGLG enhanced image to form a fused image with more details and high contrast. GLG algorithm works well for some lowcontrast images with a particularly high histogram component on the leftmost end. It fails in the cases where a particularly high histogram component is on the rightmost end and some high histogram components lie inside the histogram. These limitations and constraints are broken in proposed techniques.

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