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An Adaptive Image Contrast Enhancement Technique for Low-Contrast Images

AWAIS MAHMOOD[1], SAJID ALI KHAN[2], SHARIQ HUSSAIN[2], AND ESLAM MOHAMMAD ALMAGHAYREH[1,3]

[1]College of Applied Computer Science, King Saud University (Almuzahmiyah Campus), Riyadh 11451, Saudi Arabia
[2]Department of Software Engineering, Foundation University Islamabad, Islamabad 44000, Pakistan
[3]Department of Computer Science, Yarmouk University, Irbid 21163, Jordan

Corresponding author: Sajid Ali Khan (sajidalibn@gmail.com)

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ABSTRACT Contrast enhancement is important and plays vital role in many applications. Histogram equalization-based techniques are widely used techniques for contrast enhancement. However, it faces the contrast over-stretching, which in return causes the loss of details and unnatural look to the target image. To address this issue, this work presents a novel scheme for image contrast enhancement. The contribution of the proposed scheme is twofold. First, the image can lose many important information when an image size is decreased. For that, the image is transformed from spatial to wavelet domain so that the multi-resolution can be achieved. Second, Gamma correction is a proven technique that produces natural look and preserves mean brightness of an image with the choice of optimal gamma values. Here, Particle Swarm Optimization (PSO) is utilized to select the optimal gamma values. In this study, an effective fitness function is proposed to maximize the performance of PSO. Experimental findings show that the proposed approach improve the image contrast up to a greater extent without introducing any artifacts.

INDEX TERMS Brightness preservation, contrast enhancement, gamma correction, particle swarm optimization, wavelet domain.

I. INTRODUCTION

The contrast enhancement can be utilized as an image pre-processing technique for many uses in computer vision. There are several factors which effects the image quality such as illumination, noise and contrast changes [1]. The contrast of an image is represented as the disconnection factor between the brightest and darkest spot in an image [2]. Where, the low contrast is indicated by the smaller separation factor and the higher contrast indicates by a larger separation factor. Due to its significant importance in medical image processing, digital photography, consumer electronics, semantic segmentation [3], scene labeling [4] and underwater images, it is important before further processing to enhance the distorted image contrast.

In literature, many image contrast enhancement (CE) methods have been proposed [5]–[7]. Generally, CE technique can be classified into pixel domain [8]–[10] and transform domain [11], [12] techniques. Previous studies used pixel intensity operations for CE, while later studies implements transform domain techniques or frequency domain techniques for CE, such as wavelet [13], curvelet [14] and discrete cosine transform [15].

Numerous pixel-domain techniques exist in literature which are based on the redistribution of gray levels. Techniques based on Histogram equalization (HE) fall under the category of pixel-domain techniques [16]. Practically, HE equalizing the cumulative distribution function of histogram to implement pixel intensity mapping. HE-based techniques are widely used in literature due to their high computational efficiency, however, these tend to over enhance the contrast of the image because there is no mechanism available to control the enhancement levels. Adaptive histogram equalization (AHE) is another technique based on histograms that can enhance image contrast more effectively. AHE can preserve more image detail as compared to ordinary HE techniques. Despite its merits, over- enhancement is occurred in some portion of the image due to homogenous blocks [17]. To overcome the over-enhancement issue in homogeneous regions, Pizer *et al.* [18] proposed contrast limited

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adaptive histogram equalization (CLAHE). In CLAHE, the input image is first divided into non-overlapped sub-blocks and HE is applied to each sub-block. CLAHE is capable to attain the high contrast, however, it produces ring artifacts and also amplifies the noise in flat regions. Gamma correction is another pixel-domain technique which try to improve the brightness of dimmed images [16], however, the selection of gamma values manually is time consuming and tedious task.

Frequency domain techniques operate on transforms of the input image, such as cosine, wavelet and Fourier transforms. The basic advantage of the frequency domain methods is that it gives the spectral information about an image and are also computationally efficient [19], [20].

In recent years, many evolutionary algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been combined with CE techniques [21]–[23] to achieve the desired quality in the enhanced image. The role of such evolutionary algorithms is finding the optimal intensity parameters by maximizing the fitness (objective) function in image enhancement process.

The existing methods are incapable to enhance the image contrast and maintain the brightness of the image with different resolutions. The drawback of these methods provided motivation to design an effective method to enhance image contrast, and that work well on high as well as on low contrast images. In the proposed method, we deal with the low contrast images in frequency domain instead of spatial domain, as our objective is to enhance the contrast of low-resolution images. DWT is applied to produce the low-frequency and high-frequency components on the input image. The low-frequency component contains most of the image details whereas the high-frequency component is having the noise data. To further improve the image quality, we applied gamma correction to the low-frequency component and the high-frequency component kept unchanged. The conventional gamma correction, applied by many researchers, is not capable to enhance the globally bright images and also the local bright regions' structure in dimmed images may be lost.

Here, an evolutionary approach of gamma correction is proposed to preserve the brightness and details of the image of both brighter and low contrast images. The PSO is applied to make the gamma correction adaptive by calculating the optimal gamma values. This paper suggests a new fitness function for gamma correction which preserve both local and global information.

Some of the related works on discrete wavelet transform, gamma correction and particle swarm optimization are presented in the following sections.

A. DCT

In wavelet transform, two-channel filter bank is used to decompose the input image into multi-resolution sub-band images. The high-pass filter and low-pass filter is repeatedly applied to the image into vertical and horizontal directions in order to form multi-resolution decomposition [24]. The DWT uses scaling function (ϕ) and three wavelet function (ψ) for decomposing an image. Eq. 1 represents the 2D scaling function and Eq. 2, 3 and 4 denotes the 2D wavelet functions.

$$\phi\,(x, y) = \phi(x)\phi(y) \tag{1}$$

$$\psi^{H}\,(x, y) = \psi(x)\phi(y) \tag{2}$$

$$\psi^{V}\,(x, y) = \phi(x)\psi(y) \tag{3}$$

$$\psi^{D}\,(x, y) = \psi(x)\psi(y) \tag{4}$$

Considering the details coefficient contains most of the image noise, we keep it unchanged and only enhance the approximation coefficients using Gamma correction approach.

B. GAMMA CORRECTION

Gamma correction belongs to a family of histogram modification (HM) techniques obtained simply by adaptively changing the gamma parameter γ [25]. The simple of the transformed gamma correction (TGC) can be presented as:

$$TGC = l^{\gamma}_{\max\left(\frac{l}{l_{max}}\right)} \tag{5}$$

where γ is intensity curve and its parameter control the image stretching degree. Different parametric values of γ produce different effects on input image. For example, the input image will be brighter when $\gamma < 1$ and the enhanced image will be darker when $\gamma > 1$. Hence, it is important to select the optimal value of γ that creates images that look natural. To estimate the optimum gamma values, we have employed PSO technique in this study.

C. MOTIVATION AND CHALLENGES OF USING DWT, GC AND PSO IN IMAGE CONTRAST ENHANCEMENT

Wavelets have many advantages over other transformation techniques like Discrete Fourier transform (DFT) and Discrete cosine transform (DCT). Its ability is to simultaneously provide frequency and spatial representation of the image. Wavelet-based methods only focus on those sub-bands that contains relevant information and prune away those sub-bands with the noisy data. Wavelet-decomposition provides additional advantages of using high-frequency sub-bands to access edge features and using low-frequency sub-bands are utilized in order to bring different spatial resolution data to a common resolution. Our motivation to use DWT in this work is to only enhance the sub-band (low-frequency component) that contains the effect of illumination and keep the noisy data sub-band (high-frequency component) unchanged. This process controls the noise enhancement effectively and also provide multi-resolution analysis.

Gamma correction is well-established technique for image enhancement that can be used to preserve the image mean brightness and also to produce more natural-looking images. Although the current gamma correction approach can yield well results, however, the distortion may be occurred in some regions of the enhanced image due to inappropriate gamma values setting. Therefore, selection of the optimal gamma values is a trivial and tedious task. In proposed work, PSO is used for selection of optimal gamma values.

PSO is a swarm intelligence method which is widely used for optimization algorithm. PSO uses particles for the search of best solution out of various possible solution. PSO shares many similarities with Genetic algorithm (GA). However, unlike GA, crossover and mutation operators are not present in PSO. Compared with GAs, the computational time of PSO is less than GAs because of the quickly convergence of all particles to the best solution [25], [26]. The main challenge which need to be address when using PSO for contrast enhancement is providing appropriate objective criterion for fitness function of PSO. The objective evaluation criterion (Fitness function) plays an important and vital role in finding the best solution using the PSO.

II. PROPOSED IMAGE CONTRAST ENHANCEMENT METHOD

In this section, architecture of the proposed framework is explained and discussed thoroughly. The proposed adaptive contrast enhancement technique is described in the following steps:

Step 1: First the input image is processed through DWT to obtain the detail coefficients and approximation coefficients. As stated in many studies, that most of the illumination data is found in the approximation component and the edges are concentrated in details coefficients [27]. Hence, separating the approximation coefficients from details coefficients and enhancing only the approximation coefficients will protect the edge information.

Step 2: In the second step, adaptive Gamma correction is utilized to enhance the approximation coefficients. Usually, the Gamma correction when applied globally to contrast distorted images with fixed gamma value is not appropriate for optimal spreading of gray levels. In order to deal with this issue, in this paper we adaptively set the gamma value using PSO.

Step 3: In order to enhance image contrast, global and local information is important. Such information, however, is neglected in traditional methods for enhancing contrast image based on PSO. In the view that fitness function is critical in PSO to evaluate the image contrast based on local and global information, a new fitness function is utilized to find the most suitable gamma values. The proposed fitness function consist of three performance measures: (i) entropy (ii) root mean square (RMS) contrast (iii) sum of edge intensities.

As discussed earlier, the transform domain image can be used as low frequency and high-frequency component. The high-frequency component presents finer detail whereas low-frequency contribute to global description of an image [28]. In proposed work, the original image is first subdivided into low and high-frequency sub-bands by 1-level DWT using Haar wavelet.

The details coefficients and approximation coefficients of an image $I(x, y)$ of size MxN are obtained as [11]:

$$W_{\psi}^{i}(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=1}^{M} \sum_{y=1}^{N} I(x, y)\psi_{j,m,n}^{i}(x, y) \quad (6)$$

$$W_{\phi}(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=1}^{M} \sum_{y=1}^{N} I(x, y)\phi_{j_0,m,n}(x, y) \quad (7)$$

where $W_{\psi}^{i}(j, m, n)$ are details coefficients in horizontal, vertical and diagonal directions for scales $J \geq j_0, j = 0, 1, 2, 3 \ldots\ldots\ldots\ldots J-1$ *and* $m, n = 0, 1, 2, \ldots\ldots\ldots 2^j - 1$. In Eq. 7, $W_{\phi}(j_0, m, n)$ are approximation coefficients at arbitrary starting scale j_0 of $I(x, y)$. This procedure is 1-level DWT and the four new sub-bands are named LL, LH, HL and HH.

The LL sub-band corresponds to the low-frequency information both in horizontal and vertical direction. Similarly, the LH sub-band holds the low and high-frequency component in horizontal and vertical direction respectively. In the same way, HL and HH sub-bands are interpreted. We only processed the LL-sub-band for contrast enhancement because it holds most of the brightening data.

To enhance the contrast of the approximation component using gamma correction approach, we rewrite the TGC as:

$$W_{en} = W_{\phi}(j_0, m, n)_{max} \left(\frac{W_{\phi}(j_0, m, n)}{W_{\phi}(j_0, m, n)_{max}} \right)^{\gamma} \quad (8)$$

Actually, in real-world the contents of the low-contrast images are unknown, which need to be enhanced. In order to enhance the low-contrast image and preserve the image details, it is required to select the optimal parameters for γ which cannot be selected manually [21]. For optimal selection of γ parameters, we utilized PSO in this work.

For the problem in hand, the set of gamma values (γ) are coded as a particle in PSO.

$$\gamma = \{\gamma_1, \gamma_2, \gamma_3, \ldots\ldots\ldots\ldots \gamma_N \quad (9)$$

The solution space is covered at the start of the algorithm by generating the particle positions. Similarly, the velocity V_0^i also set randomly and then the fitness value is assigned to each particle using problem-dependent fitness function. The selection of appropriate fitness function without losing image details is a critical and challenging task.

Intuitively, the enhanced image required to have higher contrast, higher intensity of the edges and also to preserve local and global information. Inspired from these facts, we proposed a new fitness function by combining three performance measures namely: (i) entropy (ii) root mean square (RMS) contrast (iii) sum of edge intensities.

More specifically, the following fitness function is used to enhance the image contrast (denoted as C_{en}).

$$F(C_{en}) = \sqrt{\frac{E(C_{en})^2 + RMS(C_{en})^2 + EI(C_{en})^2}{3}} \quad (10)$$

where the different terms used in the fitness function are described as follows.

The entropy (first term) of the enhance image can be represented as:

$$E\left(C_{en}\right) = \sum_{i=0}^{255} h_i log_2(h_i) \tag{11}$$

In equation 11, the probability of the *ith* intensity value occurrence is denoted by h_i.

The second term $RMS(C_{en})$ represents the root-mean-squared (RMS) contrast. RMS contrast can be calculated as the standard deviation of luminance pixel divided by the whole image average luminance. It is used for the images with complex patterns such as natural images. In order to make the RMS contrast measure both local and global image quality, the image is first divided into different block and then RMS contrast is calculated. Let b is the block size of $M_b x N_b$ and $B = \{b_{0,0}, b_{1,1}, b_{2,2} \ldots\ldots..., b_{bx,by}\}$, where b_x and b_y are the number of blocks along x-axis and y-axis. Then, RMS contrast at i, j location in block $(b_{bx,by})$ can be calculated as [29]:

$$RMS_{(b_{bx,by})} = \frac{1}{M_b N_b} \sum_{i=0}^{M_{b-1}} \sum_{j=0}^{N_{b-1}} (x_{ij} - \bar{x})^2 \tag{12}$$

where $\bar{x}$ is a normalized mean of the block and x_{ij} is a normalized value such that $0 \leq x_{ij} \leq 1$. The pixel intensities from all blocks $(b_{bx,by})$ is sum to generate the weighted contrast and it can be defined by Eq. 13.

$$RMS\left(C_{en}\right) = \frac{1}{mn} \sum_{bx=0}^{m-1} \sum_{by=0}^{n-1} RMS_{(b_{bx,by})} \tag{13}$$

The contrast is measured using RMS contrast according to the spread of the histogram.

The sum of the image's edge intensities is represented by the third term $EI\left(C_{en}\right)$ in the fitness function. The enhanced image required to have larger values as compared to the low-contrast original image. In order to obtain $EI\left(C_{en}\right)$, first Canny edge detector [16] is applied and then summation of edge intensities pixels is formulated.

At the start of PSO algorithm, the velocity v_0^i and initial population is selected at random. After contrasting the initial population, each particle is assigned fitness value by evaluating the fitness function $F\left(C_{en}\right)$ at each iteration. The particle with best fitness value is stored as a global-best by comparing all the particles. This process is repeated until the condition of termination is satisfied and final optimal gamma value is found which produces enhanced image.

At the end the enhanced approximation sub-band image (W_{en}) is combined with approximation sub-bands $W_\psi^i\left(j, m, n\right)$ and then converted back to spatial transform using inverse DWT (refer to Eq. 14).

$$\begin{aligned} I^{\wedge}\left(x, y\right) &= \frac{1}{\sqrt{MN}} \sum_m \sum_n W_{en}\left(j_0, m, n\right) \phi_{j_0,m,n}\left(x, y\right) \\ &\quad + \frac{1}{\sqrt{MN}} \sum_{i=H,V,D} \sum_{j=j_0}^{\infty} \\ &\quad \times \sum_m \sum_n W_\psi^i(j, m, n) \psi_{j,m,n}^i(x, y) \end{aligned} \tag{14}$$

The detail procedure containing the steps for contrast enhancement is presented in Algorithm 1.

TABLE 1. Parameter settings for PSO.

PSO Parameter	Value
Swarm Size	50
Inertia Weight ω	0.6
Learning Factors c_1, c_2	$c_1 = 2, c_2 = 2$
Number of Iterations	100

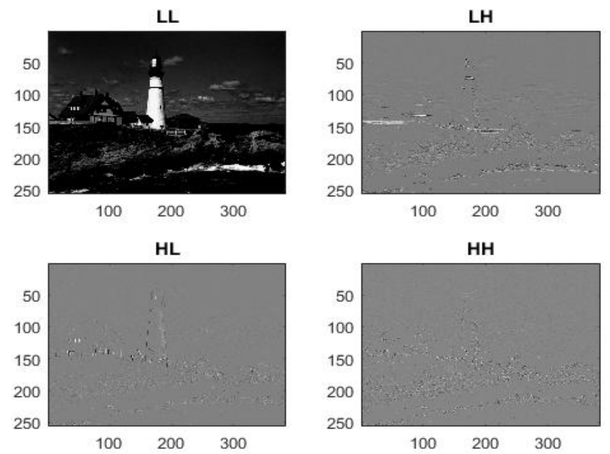

FIGURE 1. Result of 1 level DWT.

III. EXPERIMENTS

The proposed framework is implemented in MATLAB. The Kodak test image dataset [30] which contains 24 color images is used to test the proposed technique. All the images are first converted to gray-scale for performance evaluation. In order to produce both low-contrast and high-contrast image, we further used GNU Image Manipulation Program (GIMP) [31].

Table 1 shows the parameters to control the PSO for better results. Initially we have chosen 50 particles for searching the optimal parameters of gamma. The initial velocity and population are chosen randomly. The inertia weight (ω) parameter plays a major role in regulating the current and previous velocity of the particles. We also noted in this work that searching ability of PSO and inertia weight (ω) is directly proportional.

The quantitative evaluation is an important step after contrast enhancement to check that how well the image is enhanced. In this work, used four well-known image quality criterions which have widely used for assessment of the image quality. These quality criterions include: (i) Entropy [32] (ii) Absolute Mean Brightness Error (AMBE), (iii) Peak Signal-to-Noise Ratio (PSNR) and (iv) No-Reference image quality metric for contrast distortion (NIQMC) [33].

One level DWT is used to divide the original image I into four sub-bands known as LL, HL, LH and HH. Fig. 1 illustrate the result of one level DWT.

Algorithm 1 The Procedure for Image Contrast Enhancement

Input: Input image (I) with size MxN
Output: Output image (I_e)
Procedure
1: Decompose the original image (I) into wavelet domain to generate approximation component (W_ϕ) and detail component ($\mathrm{W}^{\mathrm{i}}_\psi$) using Eq. (6 and 7)
2: Apply adaptive gamma correction using equation (8) to generate W_{en}
3: Apply PSO (step 4 to 19) for selection of gamma value (γ)
4: Initialize the PSO Parameters
5: **While** Termination criterion was not satisfied **do**
6:     **For** each iteration **do**
7:         **For** each $Particle(\gamma_N)$ **do**
8:             $F\ (C_{en}) = Fitness\ function\ (\gamma_N)$
9:             **If** $F\ (C_{en}) > fitness(pbest)$
10:                 $pbest = Particle$
11:             **end if**
12:             **If** $F\ (C_{en}) > fitness(gbest)$
13:                 $gbest = Particle$
14:             **end if**
15:             update velocity: $v_i\ (t+1) = \omega v_i\ (t) + c_1 r_1\ (P_i\ (t) - x_i\ (t)) + c_2 r_2 (P_g\ (t) - x_i\ (t))$
16:             update position: $x_i\ (t+1) = x_i\ (t) + V_i(t+1)$
17:         **end for**
18:     **end for**
19: **end while**
20: **return** W_{en}
21: Apply inverse DWT transform using Eq. 14 to produce final enhanced image

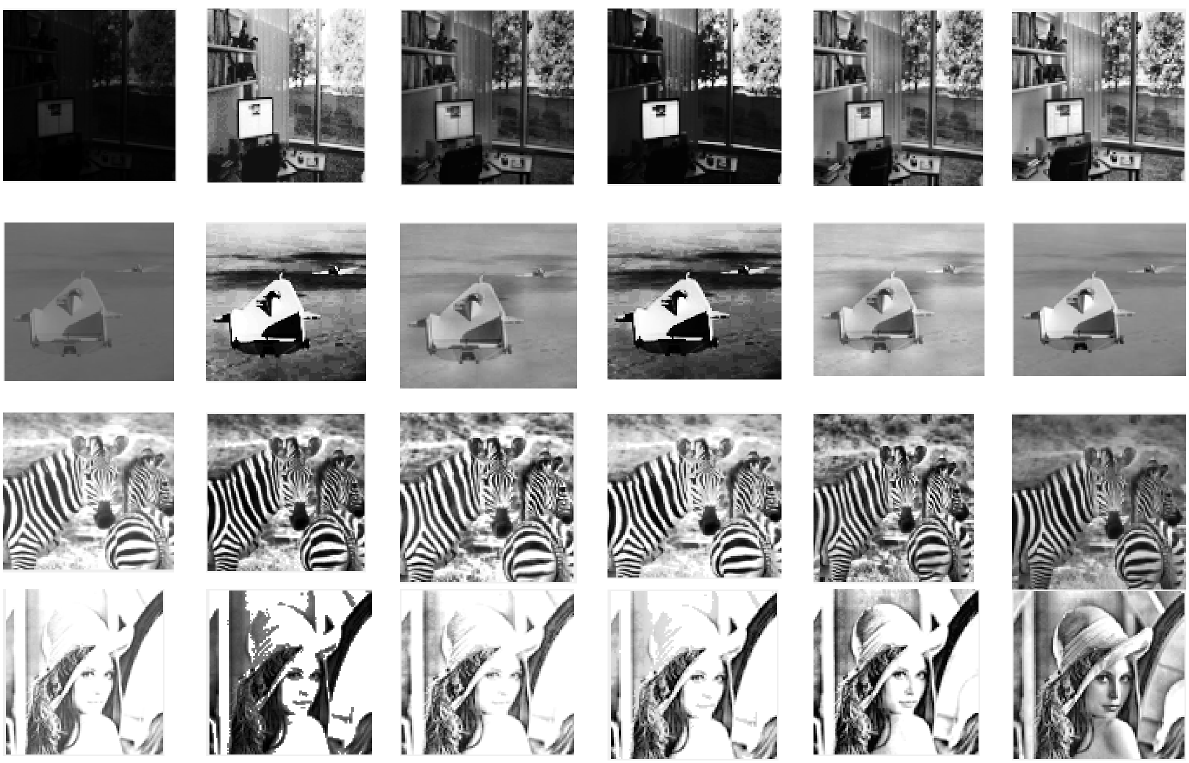

FIGURE 2. **The visual quality results obtained by HE (first column), CLAHE (second column), BBHE (third column), BPDFHE (fourth column) and proposed method (fifth column).**

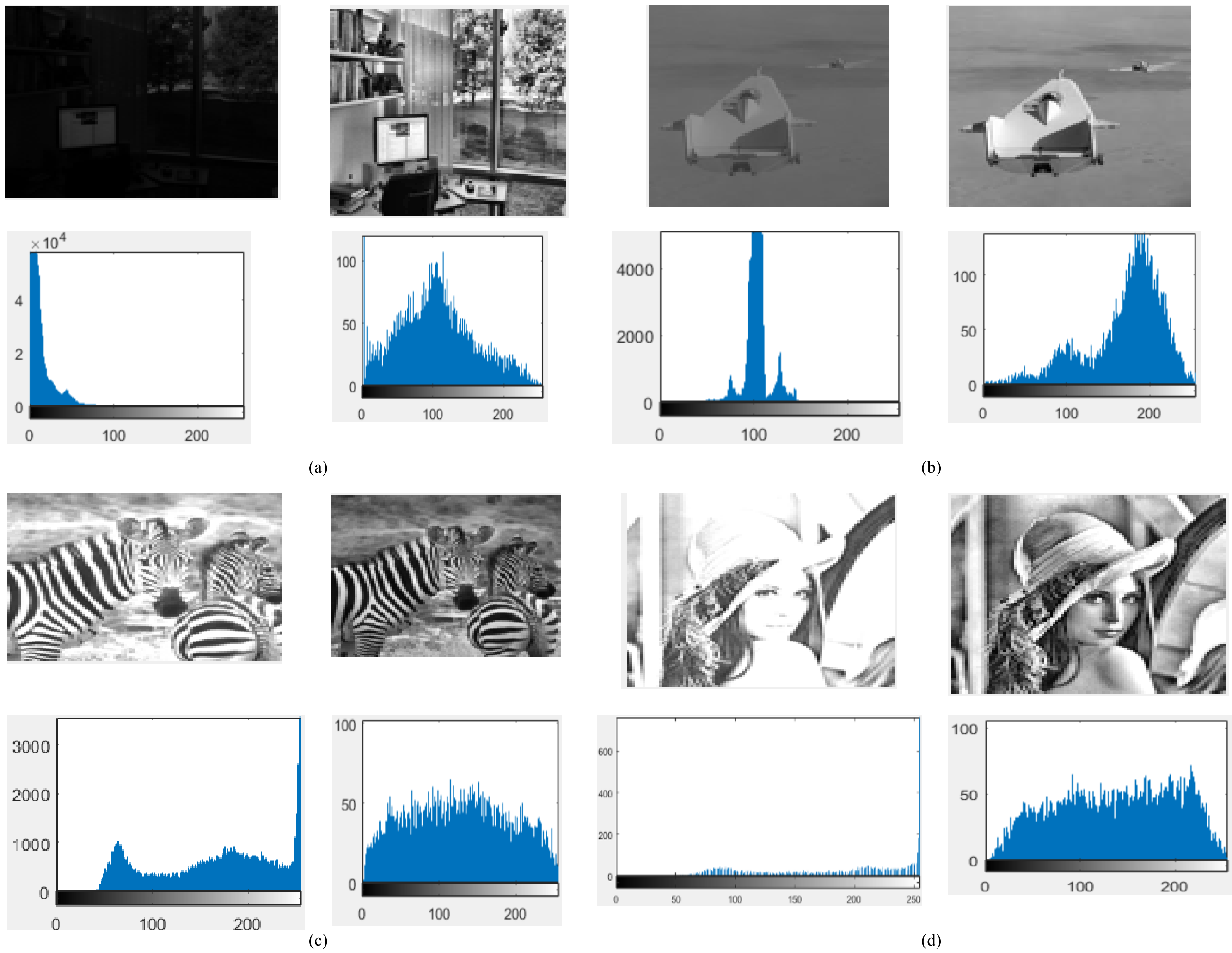

FIGURE 3. The mean values preservation of the proposed method. (a) Office. (b) Lifting body. (c) Zebra. (d) Lena.

After that image of LL sub-band is processed with Gamma correction method. PSO is utilized for optimal parameter selection of gamma correction. Finally, inverse DWT has been used to get the enhanced image. In this study, two types of experiments were conducted to test the proposed method.

In the first experiment, compared the findings of the suggested framework with state-of-the-art approaches such as HE, CLAHE, Bi-histogram equalization (BBHE) [34] and Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) [35]. Fig. 2 illustrate the assessment of the visual quality of the images after applying above mentioned methods. All the images processed by conventional image enhancement methods show the over-enhancement and brightness degradation. There is not much brightness change observed in the zebra image because the original image is not significantly degraded. The results of BPDFHE is better than HE, CLAHE and BBHE. Furthermore, the details in the dark image (office image) and in the brighter image (Lena image) after enhancement is very clear. Similar analysis can be done for dull image like lifting body.

Mostly, the output image of enhancement techniques based on HE is invariable to mean change due to intensity values redistribution. The proposed method, however, is capable of preserving the input image mean as shown in Fig. 3. It is apparent from the Fig. 3 that the procedure adopted by the proposed method gives the mean values which preserve the brightness of the image.

We quantitatively assess the performance in second experiment of the above-mentioned methods with respect to PSNR, AMBE and Entropy. Table 2 shows the comparison of AMBE, PSNR, Entropy values and NIQMC of the proposed method with HE, CLAHE, BBHE and BPDFHE. The results indicate that the proposed method achieved highest score of PSNR for all the test images as compared to other methods. The calculated average value of PSNR is high thus indicate the absence of noise in the enhanced image. This indicates that the approach suggested is better to improve the contrast. It is also noted that the results of BPDFHE method in terms of PSNR values is better than HE, CLAHE and BBHE. However, in case when input image is dull like lifting body

TABLE 2. Results of PSNR, AMBE and Entropy for assessment of contrast enhancement and brightness preservation.

Measure	Image	HE	CLAHE	BBHE	BPDFHE	Proposed
PSNR	Office	5.57	10.80	12.40	15.90	24.80
	Lena	10.10	15.90	18.20	21.40	29.70
	Lifting body	10.50	14.10	11.50	10.20	19.60
	Zebra	10.30	15.40	19.80	24.30	31.70
AMBE	Office	116.80	60.90	52.20	40.70	22.40
	Lena	53.40	13.50	12.10	9.70	5.87
	Lifting body	26.70	42.80	15.70	34.50	8.64
	Zebra	44.70	37.4	13.90	10.40	6.91
Entropy	Office	4.61	7.24	7.80	8.40	9.88
	Lena	3.69	5.00	4.46	5.88	6.99
	Lifting body	4.74	6.32	4.84	6.76	8.33
	Zebra	5.77	6.98	7.06	8.47	9.66
NIQMC	Office	4.98	2.97	3.23	3.33	4.64
	Lena	5.66	4.12	4.44	4.98	5.24
	Lifting body	4.57	3.35	3.89	4.22	4.98
	Zebra	4.23	3.91	4.24	4.25	5.32

image the results of CLAHE become better as compared to other methods.

In order to preserve the image brightness, it is required that the value of AMBE must be small because the high values indicates an excessive change in gray levels. Such change in gray levels degrade the image quality. It is clear from the review of the findings that the proposed method also preserved maximum brightness as compared to HE, CLAHE, BBHE and BPDFHE methods. After applying the HE to the input images, the brightness of the images is increased, however, the image brightness is not preserved due to highest value of AMBE. Similarly, the proposed method obtained higher entropy for all the test images which indicates the proposed method is best in details richness, whereas the entropy values are less for other HE techniques. Moreover, NIQMC takes the advantage of both global and local aspect of the image. The larger value of NIQMC indicate the better image quality contrast. The high results of NIQMC performance metrics shows that our proposed method preserved both local and global image information. NIQMC particularly favor the images with high contrast. From the results, it can be seen that HE have the higher value of NIQMC because it over-enhanced the image contrast.

Hence, the visual and quantitative results proved that proposed method enhanced the image contrast and also preserve the image brightness which helps to avoid the artifacts present in other methods.

Furthermore, Table 3 presents the average performance using the whole Kodak dataset. For AMBE, the lower value indicates better results, however, the larger values of PSNR, Entropy and SSIM represent good results. For fair comparison, we have implemented the methods proposed in [36]–[43]. In [36], the authors used sigmoid function to

TABLE 3. The proposed method performance comparison with existing methods using the Kodak image dataset (as a whole).

Method	PSNR	AMBE	Entropy	SSIM	NIQMC
Ref. [47]	13.79	31.55	6.22	0.86	0.414
Ref. [48]	16.26	40.14	7.58	0.79	0.489
Ref. [49]	13.56	38.78	5.56	0.85	0.432
Ref. [50]	17.78	29.73	8.21	0.72	0.556
Ref. [22]	24.66	16.46	9.97	0.95	0.598
Ref. [36]	27.49	17.68	8.64	0.86	0.614
Ref. [37]	28.45	16.78	8.34	0.79	0.523
Ref. [38]	15.25	36.45	7.19	0.74	0.477
Ref. [39]	16.46	28.45	7.97	0.81	0.496
Ref. [40]	25.13	19.78	7.41	0.71	0.564
Ref. [41]	27.36	14.72	8.34	0.89	0.647
Ref. [42]	26.24	15.45	8.24	0.84	0.663
Ref. [43]	25.97	13.54	7.98	0.81	0.634
Ref. [44]	29.43	13.73	7.34	0.92	0.654
Ref. [45]	26.47	14.87	7.22	0.88	0.639
Ref. [46]	27.33	13.89	8.11	0.85	0.624
Proposed Method	31.44	11.24	10.40	0.98	0.714

increase the contrast. Afterward, the multi-objective PSO and gamma correction is applied to maximize the information content and preserve the image intensity respectively. As seen from the results, the proposed method outperforms other methods by obtaining the best results. Kumari *et al.* [37] used lifting–stationary wavelet transforms to enhance image's contrast having low resolution. A weighted histogram distribution-based adaptive gamma correction is proposed [38] to improve the image detail and preserve the natural look of an image. Later, Kansal and Tripathi [41] also introduced an adaptive gamma correction in which they change the value of gamma for each image. In another simple method [39], the authors combined CLAHE with different filters in order to enhance the image contrast and also to reduce the noise. Vishwakarma and Goel [40] used CLAHE along with logarithm transform for image contrast enhancement. Palanisamy *et al.* [42] proposed a hybrid approach for image contrast enhancement that combines singular value equalization, gamma correction and CLAHE. Recently, Kandhway and Bhandari [43] proposed an adaptive thresholding based sub-histogram equalization method to preserve the mean brightness and improve the contrast enhancement. In [44], Kuang et al. suggested a neural network to enhance the image contrast and reveal the image details. They also incorporated the conditional generative adversarial network for further enhancement of image contrast and to avoid the background noise amplification. Li *et al.* [45] proposed a naturalness enhancement algorithm for low light and non-uniform images by combining the histogram equalization and Retinex. The emphasis of this method is on perceptual contrast while reducing the over-enhancement, clipping effects and reducing halo artifacts. The bright region contrast is improved and preserved by means of Retinex based lightness correction method. Bilateral Filtering (BF) is utilized to suppress the halo artifacts while certain constraints are imposed to reduce the clipping effect. Moreover, they adopted perceptual contrast enhancement in order to adjust the dynamic range and also enhances the perceptual contrast without being over-enhanced. A fusion model based on variability is proposed in [46] for enhancement of image contrast with non-uniform images. They obtained a globally enhanced image and locally enhanced image based on globally contrast enhancement method, and hue-preserving local contrast enhancement method respectively. Finally, utilized a variational-based fusion model to obtain enhanced results.

Table 3 shows and portray the excellence of the proposed method as compared to existing methods. Here, the desired requirement of simultaneous contrast enhancement and brightness preservation is achieved for brighter and dark images. The inability of the existing methods can be easily noted, as the contrast is enhanced slightly on the cost of more information loss (entropy value is reduced). Although the combination of gamma correction with CLAHE is useful in some cases for contrast enhancement, still not found so efficient for dark images in terms of brightness preservation.

Digital images captured in real-world usually suffer from limited pixel sampling due to large distance between camera and human faces which cause small resolution. There is a need to restore such type of images for further analysis. For further performance evaluation of proposed method with different resolution, the initial picture size is reduced by half. The results in Table 4 shows that the proposed method performance is not significantly degraded when the image size is reduced.

We have also evaluated the algorithmic complexity of our proposed method. Our proposed method contains wavelet decomposition, contrast enhancement through gamma correction and the optimal k-gamma value selection using PSO. In wavelet decomposition stage, the input image is divided into four sub-bands each of size $\frac{N}{2}$ hence the complexity can be calculated as:

$$DWT = O(4N^2 LogN)$$

The complexity of the gamma correction can be calculated as follow:

$$Gamma\ correction = NLogN$$

Due to stochastic nature of PSO, single run for computational complexity would not be sufficient enough to guarantee the correctness of time complexity. In this regard, $N = 100$ independent runs with the same random data-set has been executed on constant parameter settings to find out the mean execution time to see the computational complexity in terms of time. Following relation has been developed to find out the mean execution time (MET).

TABLE 4. Results of PSNR and AMBE for assessment of contrast enhancement and brightness preservation with reduced image size.

Measure	Image	HE	CLAHE	BBHE	BPDFHE	Proposed
PSNR	Office	4.20	7.56	8.56	10.20	21.50
	Lena	7.42	10.47	13.50	15.45	27.20
	Lifting body	7.32	9.65	7.56	7.45	16.50
	Zebra	6.88	10.36	13.50	18.40	28.40
AMBE	Office	122.30	68.40	59.70	51.60	26.40 - 22.40
	Lena	60.74	18.90	25.60	20.60	8.40 - 5.87
	Lifting body	36.24	54.20	27.40	42.30	13.50 - 8.64
	Zebra	53.47	45.78	24.30	23.20	9.90 - 6.91

$$MET = \sum_{i=1}^{T}\sum_{j=1}^{P}\frac{F_i}{N} \cong O(N^2)$$

where $\boldsymbol{T}$ and $\boldsymbol{P}$ represent the iteration and particles respectively.

The overall complexity can be formulated by the following equation:

$$Total\ complexity = O\left(4N^2 LogN\right) + NLogN + O\left(N^2\right) \cong O\left(N^2 LogN\right) \quad (15)$$

We can see from the results that the proposed method achieved the balance between image distortion and contrast improvement. The proposed method gained more contrast enhancement and while less distortion is incurred. However, due to use of PSO the time complexity of the proposed method increased.

IV. CONCLUSION

An image contrast-enhanced method is proposed in this paper that overcome the drawback of the existing methods. The main contribution of this work relies on the following aspects: 1) The proposed method holds more information and also provide multi-resolution analysis, 2) The proposed method enables the user to enhance the image contrast while preserving the image brightness. For this, a new objective function is introduced which achieved both objective performance and visual quality measures. The experimental results demonstrate that the proposed method out-perform existing methods.

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AWAIS MAHMOOD received the B.S. and M.S. degrees from Eastern Mediterranean University, TRNC, Turkey, in 2001 and 2003, respectively, and the Ph.D. degree from King Saud University, Saudi Arabia, in 2014, all in computer engineering. He is currently an Assistant Professor with the College of Applied Computer science, King Saud University (Al muzahmiyyah Branch), Riyadh, Saudi Arabia. His research interests include image and speech processing, signal processing for healthcare, data science and big data processing, and software systems.

SAJID ALI KHAN received the M.S. degree and the Ph.D. degree in computer science from the Shaheed Zulfikar Ali Bhutto Institute of Science and Technology (SZABIST), Islamabad, Pakistan, in 2012 and 2019, respectively. He is currently an Assistant Professor with the Department of Software Engineering, Foundation University, Rawalpindi, Pakistan. His research interests include image processing and pattern recognition. He published number of research articles in journals and conferences of international repute. He has also been serving in board of reviewers of different international research journals and conferences. He is also serving for *SN Applied Science Journal* as a Guest Editor and an Editorial Board Member.

SHARIQ HUSSAIN received the master's degree in computer science from PMAS Arid Agriculture University, Rawalpindi, Pakistan, in 2007, and the Ph.D. degree in applied computer technology from the University of Science and Technology Beijing, China, in 2014. Since 2014, he has been with the Department of Software Engineering, Foundation University Rawalpindi Campus, where he is currently an Assistant Professor. His main research interests include web services, QoS in web services, web service testing, the IoT, and e-learning. He served as a Workshop/Special Session Co-Chair for the IEEE International Conference on Internet of People 2018 (IoP 2018) and publicity Chair for the IEEE International Conference on Internet of People (IoP 2015). He is an Editorial Board Member of the *Journal of Next Generation Information Technology* (JNIT)—AICIT, South Korea.

ESLAM MOHAMMAD ALMAGHAYREH was born in Irbid, Jordan, in 1979. He received the B.S. and M.S. degrees in computer science from Yarmouk University, Irbid, in 2001 and 2003, respectively, and the Ph.D. degree in computer science from Concordia University, Montreal, QC, Canada, in 2008.

In 2003, he was a Lecturer with the Department of Computer Science, Yarmouk University. From 2003 to 2008, he was a Ph.D. student and a Research Assistant with the Department of Computer Science, Concordia University. In 2008, he joined the Department of Computer Science with Yarmouk University, as an Assistant Professor, where he has been promoted to the rank of an Associate Professor and he is still a Faculty Member, since 2013. In 2014, he has also joined the College of Applied Computer Science at King Saud University, KSA, as an Associate Professor of Computer Science. He is the author/editor of three books and more than 25 articles. His research interests include distributed systems, computational intelligence, and runtime verification of distributed programs and data science.