Tri-modal technique for medical images enhancement

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ABSTRACT

Owing to methods of acquisition, medical images often require enhancement for them to serve the intended purpose of computer-aided diagnosis. Most medical image enhancement techniques are application specific, leading to the introduction of different enhancement methods for different medical images. In addition, the execution time of most of the previous enhancement methods is longer than necessary. Hence, there is a need for a method that produces fast and satisfactory results when deployed for the enhancement of several medical images. This paper proposes a tri-modal technique, involving a hybrid combination of unsharp masking, logarithmic transformation, and histogram equalization approaches, for medical image enhancement. Three classes of medical images: X-ray, magnetic resonance, and computer tomographic images are used for the evaluations of the proposed tri-modal method, where absolute mean brightness error, peak signal-to-noise ratio, and entropy are utilized as performance metrics. Both qualitative and quantitative evaluations reveal that the proposed tri-modal method performed better than the four previous methods in the literature for the three classes of medical images used in the evaluation. Also, the execution time of the tri-modal technique compares well with those of mono-mode methods. Thus, the tri-modal technique produces better enhanced medical images from different medical image inputs.

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1. INTRODUCTION

Medical images are images of organs or body parts (usually internal) used for disease diagnosis, study, and identification. Several medical images exist, depending on the modality used in their obtainment. The list includes X-ray [1]–[3], computed tomography (CT) scan [4], [5], magnetic resonance imaging (MRI) [5], ultrasound [6] and positron emission tomography (PET) [7]. Nowadays, medical images are playing important roles in disease identification, critical surgery operations, pregnancy complication monitoring, early diagnosis, and severe disease screening [2]. Low contrast which degrades the image quality constitutes the main issue with medical images, thus, enhancing such images is a must for suitability for the intended purposes. The main objective of medical image enhancement algorithms is to reconstruct and make the recorded image to be similar as much as possible to the true picture in order to aid proper diagnosis and therapy. Since medical images are produced via the use of one or combination of radiation mechanism, sound waves propagation, magnetic field resonance effect and other electromagnetic effects which often lead to images with poor contrast, weak edges, blurriness and hidden diffraction patterns due to darkness, and wash out appearance in some parts of the images (when pixels are not well spread to span across the whole dynamic range of the image), enhancement of medical images become a necessity. Over the years, several biomedical image enhancement techniques have been proposed. Notable among them include un-sharp masking (USM) [8], [9], histogram equalization (HE) and its variants [8], [10]–[19], wavelet transform [11], [19]–[22], fuzzy logic-based [8], [23], neuro-fuzzy method [8], contrast stretching [8], threshold transformation [8], log transformation [8], local enhancement [8], multi-scale retinex-based [24], image size dependent normalization [25], adaptive gamma correction based algorithm [26], feature-based image fusion technique [27], discriminative low-rank sparse dictionaries learning [28], fractional order and directional derivatives [29], combined wavelet and histogram equalization [30], and adaptive thresholding combined with unsharp masking [31].

In Frosio *et al.* [9], it was demonstrated that the un-sharp mask technique can be easily applied in conjunction with median filtering to efficiently enhance X-ray images in real time. Also, the technique can be used in Cephalometric radiography to enhance under-exposed bony structures [9]. Contrast-limited adaptive histogram equalization (CLAHE), which is a form of adaptive histogram equalization (AHE) has been shown to effectively limit noise in images [12]. Bone fracture image enhancement using CLAHE was carried out in [13], the results of which showed that CLAHE gives better results than other HE variants although it took a long time. A medical image enhancement method based on wavelet transform was proposed in [20] where the coefficients of wavelets were merged to obtain a better-quality fused image. A three-dimensional wavelet transform-based biomedical image enhancement method was proposed in [21]. In that submission, a shape function was applied to the image to realize an increase in the image edge's quality. The gray image enhancement techniques are mainly histogram equalization methods based. However, the drawbacks of these methods include over-enhancement, level saturation, and increased noise level. To address these problems, approaches such as brightness-preserving bi-histogram equalization (BBHE) [19] and dualistic sub-image histogram equalization (DSIHE) [19] were proposed. Although the use of BBHE and DSIHE yielded enhanced images, it, however, failed to remove the impulse noise in the images. Color image enhancement on the other hand often involves the use of the AHE [20] technique that is at improving the overall dynamic range of the images and further enhancement of the luminance component through adaptive saturation feedback. In gray image enhancement technique, sharpening of the edges is obtained using Laplacian filter followed by AHE that overcomes the drawbacks of the conventional methods.

A comparative review of common and existing image enhancement techniques was presented in [8]. Considered methods are HE, AHE, fuzzy logic technique, neuro-fuzzy system, un-sharp masking, contrast stretching, threshold transformation, log transformation, and local enhancement. While HE presents a very simple approach to image enhancement, the performance is far from satisfactory. The AHE, which is an improvement over traditional HE has the advantage of faster operation, making it simple based on a transform adaptive histogram. The fuzzy logic method employed a fuzzy rule-based approach in the formulation of an expert system in a comprehensive way. It presents a good mathematical framework to deal with the uncertainty of information, which is typical of an image problem. In the neuro-fuzzy system method, the neural network is used for the identification of noise via the use of statistical parameters of the image while fuzzy logic is employed in the enhancement of the image. Un-sharp masking presents a simple technique in which a fraction of the high-pass filtered image is added to the original one to form the enhanced image. It has two major drawbacks: the noise present in the image is equally enhanced and the resultant sharp transition often leads to excessive overshoot on sharp edges. The CS algorithm involves stretching the pixel values of a low-contrast image or high-contrast image by extending the dynamic range across the whole of the image spectrum while threshold transformations are particularly useful for image segmentation in which isolation of an object of interest from a background. The log transformation performs better in the enhancement of image details in the darker regions of the image at the expense of detail in the brighter regions.

Most of the aforementioned methods are specialized in the techniques used in capturing the images. In addition, they often fail in producing satisfactory images due to reasons that can be traced to over-enhancement which leads to a loss of details [8]. This implies that an enhancement method that did a nice job on a particular medical image type might not produce satisfactory results on other types of medical images. Furthermore, the execution time of most of these methods is longer than necessary. Thus, there is a need for a method that produces fast and satisfactory results. These two needs combined form the basis of this research that is aimed at the development of a tri-modal method for the enhancement of a wide range of medical images.

The proposed solution is a tri-modal method that cascades three different existing methods into one for the enhancement of medical images. The proposed algorithm will be suitable for both grey and color image enhancement and does not require specification or adjustment of parameters for its operation.

2. METHODS ADOPTED IN THIS RESEARCH WORK

This research work employs three different enhancement techniques to enhance biomedical images. The first method is USM, which is used in sharpening the image via enhancement of the edges thereby removing blur that might be inherent in the image. The obtained output from the USM serves as the input to logarithm transformation (LT) which is aimed at increasing the brightness of dark pixels in the image and improving its dynamic range. The LT stage is expected to bring out some of the hidden details. Lastly, the output of the LT will serve as input to the AHE technique which is expected to improve the contrast of the image. The output of the AHE stage represents the final output of the proposed tri-modal medical image enhancement scheme. The sequence method is coined as USM-LT-AHE medical image enhancement technique. The choice of these methods is informed by their relative advantages over others, which include simplicity in terms of mathematical complexity, robustness, and fastness.

The research entails two image processing areas namely, image de-blurring and contrast enhancement. The USM is employed for image de-blurring (blur removal/sharpening) while both the LT and AHE are utilized for contrast enhancement of the sharpened image from USM. A brief description of each of the three components of the tri-modal enhancement scheme for medical images is discussed next, beginning with the USM method.

2.1. Un-sharp masking

USM enhances small structures and brings out the hidden details in the image by using un-sharp masking. It only sharpens the areas, which have edges or lots of details. USM is performed by generating a blurred copy of the original image by using a Laplacian filter. The output of the filter (blur copy of the original image) is subtracted from the original (input) image to restore the gray tones lost by using Laplacian (because the center coefficient of Laplacian spatial mask is negative). Mathematically, an un-sharp masking image is generated using (1).

$$Z(n,m) = X_0(n,m) - X_b(n,m) \tag{1}$$

Where $Z(n,m)$ the un-sharp is a masking image; $X_0(n,m)$ is the original image and $X_b(n,m)$ is the blurred copy from the Laplacian filter (also known as the correction signal).

Multiplication of the above un-sharp masking image by a fractional value (K) and the addition of the product to the original image yield the image that will be contrasted. The result is the production of a sharper and more detailed image because the small features in the image are enhanced.

$$Y(n,m) = X_0(n,m) + K\,Z(n,m) \tag{2}$$

Where $Y(n,m)$ is the output image and K is a positive scaling factor that controls the level of de-blurring or sharpness achieved at the output. Logical values for K varies between 0.2 and 0.9 [14].

2.2. Logarithmic transformation

A logarithmic transformation algorithm is used to map a narrow range of low gray values to a wider range of gray levels. When applied to the digital image, it maps the dark intensity values to higher or brighter values, which makes the details present more visible. In other words, by applying LT on images, the lower pixels are mapped into a higher pixel with higher pixels left least affected. Application of the LT algorithm results in an image of higher brightness and contrast as the output. The output image from this algorithm has values in the range of 0-1. The mathematical implication of the algorithm is (3).

$$S = C \times \log(r+1) \tag{3}$$

Where r is the input image and

$$C = \frac{\text{max}imum\ pixel\ of\ the\ input\ image}{\log(1+\text{max}imum\ pixel\ of\ the\ input\ image)} \tag{4}$$

2.3. Adaptive histogram equalization

The histogram of a digital image is the plot of the number of pixels n_k against the intensity value k, which ranges between 0 and L such that $L = 2^x - 1$ provided x is the number of bits per pixel (class unit) of the image. For this paper, images of class unit 8 are used so that $L = 2^8 - 1 = 255$. This implies the dynamic brightness range is between 0 (black) and 255 (white) to give 256 intensity levels.

Normalizing the histogram gives the probability density function which is expressed as (5).

$$p(r_k) = \frac{n_k}{n} \quad (5)$$

Where n is the total number of pixels in the image.

The histogram equalization automatically determines a transformation function that produces an output image with a uniform histogram. Such equalization transformation is denoted mathematically as (6).

$$S_k = T(r_k) \quad (6)$$

Where S_k is the cumulative density function that is defined as (7).

$$S_k = \sum_{j=0}^{k} p(r_j) \quad (7)$$

From (7) it is obvious that

$$S_k = \sum_{j=i}^{k} \left(\frac{n_j}{n} \right) \text{For } k = 1,2, \cdots L \quad (8)$$

S_k is interpreted as the intensity value in the output image that corresponds to the value of r_k in the input image. Through the application of the transformation procedure describe above, histogram equalization maps the input image into the entire range $0,1, \cdots L$ using the cumulative density function, $S_k$as the transfer function to arrive at an image with a better contrast [32].

2.4. Algorithm evaluation

Both subjective and objective approaches are employed in the evaluation of the performance of the proposed tri-modal image enhancement scheme. For subjective evaluation, output images using the proposed tri-modal enhancement scheme are visually inspected by radiologists and benchmarked with results of other enhancement methods available in the literature. The opinion score of enhanced images from the different methods is used as the basis of evaluation. The method having the highest percentage opinion score is adjudged the best. For objective evaluation, quantitative metrics used are absolute mean brightness error (AMBE), peak-signal-to-noise-ratio (PSNR), entropy, and execution time.

3. RESULTS AND DISCUSSION

The proposed tri-modal image enhancement method is implemented in MATLAB R2018a environment installed on Dell Intel core i3-2328M, 64-bit, 2.2 GHz, 4 GB RAM laptop running Windows 7 OS. Image processing toolbox functions such as *imfilter, adapthisteq, and rgb2hsv* are utilized in the implementation. To evaluate the performance of the proposed method, nine test medical images are used namely: three X-rays, three MRI, and three CT images. The low-resolution test medical images are sourced from the internet. It is worth pointing out here that in each case, two grey scales and one colored image are selected. For X-ray images, the grey scale used is images of a human leg and human right-hand fingers while the colored image was that of a slice of a human ankle. MRI images comprised of greyscale slices of the human head and the stomach; with a slice of the human head employed as a colored image. In the CT scan category, the two greyscale images are those of the human chest (bright and dark versions) while the scanned image of the liver was used as a colored CT scan test image.

For benchmarking, four other methods in the literature, for image contrast enhancement are employed. The methods are conventional HE, CLAHE, wavelet transform-based (WT) method, and fuzzy-based method. What follows are the results of the evaluations beginning with those of X-ray images.

3.1. Simulation results

Figures 1-3 show simulation results using the X-ray images while Figures 4-6 depict those of MRI scan images. In Figures 7-9, results obtained when CT scan images are used are presented. In each case of Figures 1-9, Figures (a) is the original test images, (b) enhanced images using the HE method, (c) image obtained via the use of the CLAHE method for enhancement (d) images enhanced using WT method, (e) resultant images after enhancement by fuzzy-based method, and (f) output images when enhanced by the proposed tri-modal method.

The simulated enhanced output images, from each of the four existing methods (HE method, CLAHE method, WT method, fuzzy-based method) in the literature as well as those obtained using the proposed tri-modal method, as illustrated in Figures 1-9 are placed side by side for comparison. Ten anonymous clinical inspectors are asked to assess and pick a preferred image that closely matched the original image, in each case of Figures 1-9. Table 1 portrays the results of the opinion poll on simulated enhanced images.

Figure 1. Simulation results using grey scale X-ray image of a human leg (a) original image, (b) HE method, (c) CLAHE method, (d) WT method, (e) fuzzy-based method, and (f) tri-modal method

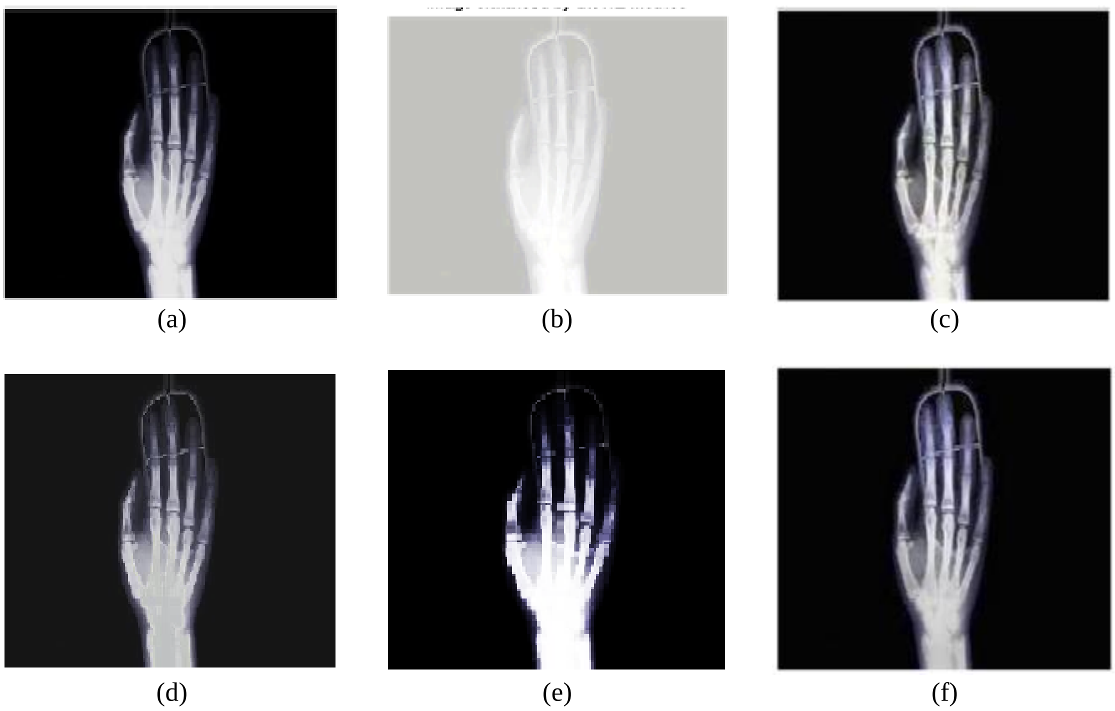
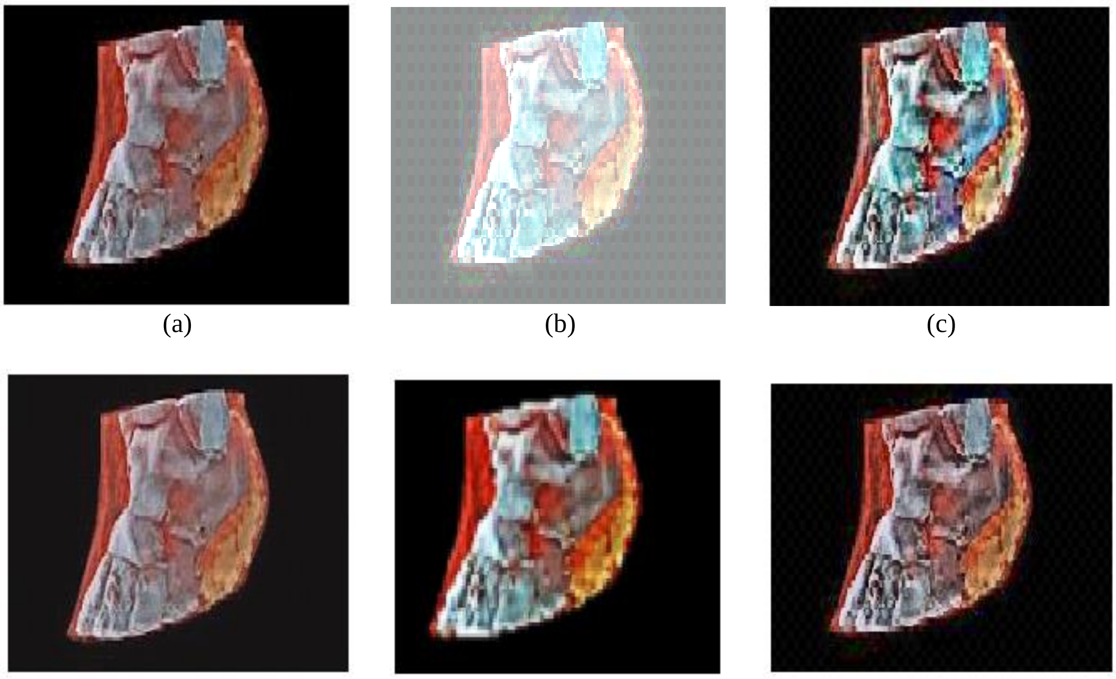


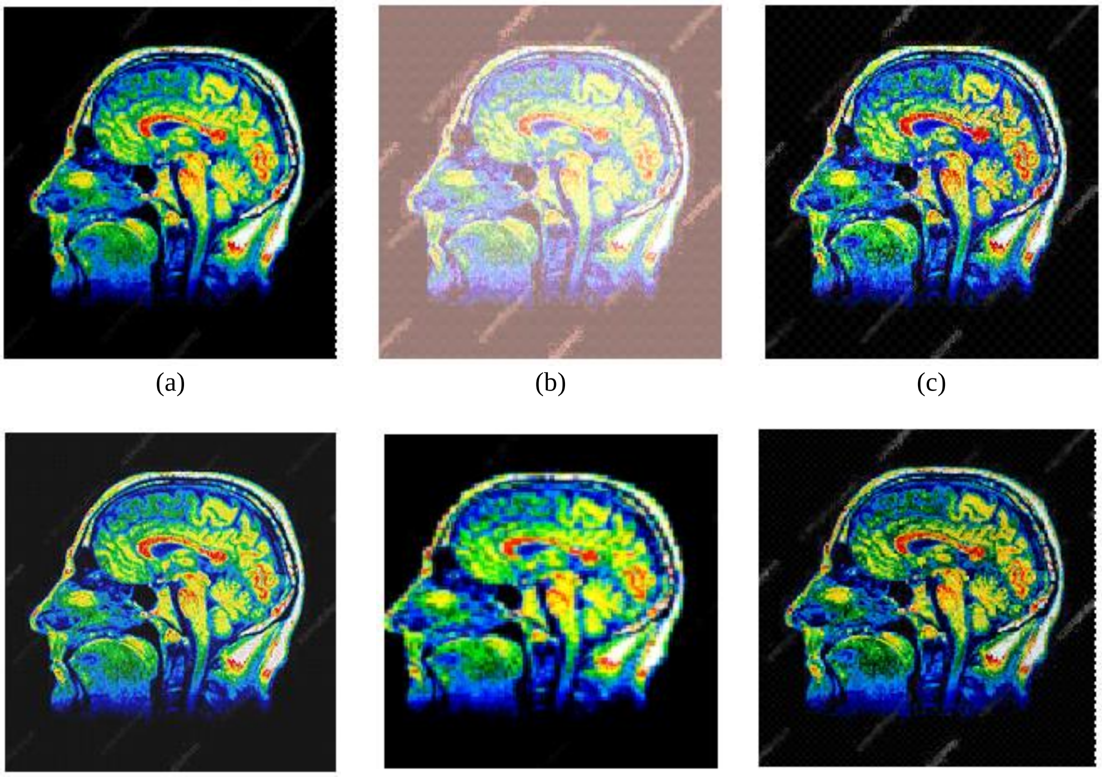
Figure 2. Simulation results using grey scale X-ray image of a human hand (a) original image, (b) HE method, (c) CLAHE method, (d) WT method, (e) fuzzy-based method, and (f) tri-modal method



(a) (b) (c)

(d) (e) (f)

Figure 3. Simulation results using colored X-ray image of a slice of a human ankle (a) original image, (b) HE method, (c) CLAHE method, (d) WT method, (e) fuzzy-based method, and (f) tri-modal method



(a) (b) (c)

(d) (e) (f)

Figure 4. Simulation results using colored MRI image of a slice of a human head (a) original image, (b) HE method, (c) CLAHE method, (d) WT method, (e) fuzzy-based method, and (f) tri-modal method

Figure 5. Simulation results using grey scale MRI image of a human stomach (a) original image, (b) HE method, (c) CLAHE method, (d) WT method, (e) fuzzy-based method, and (f) tri-modal method

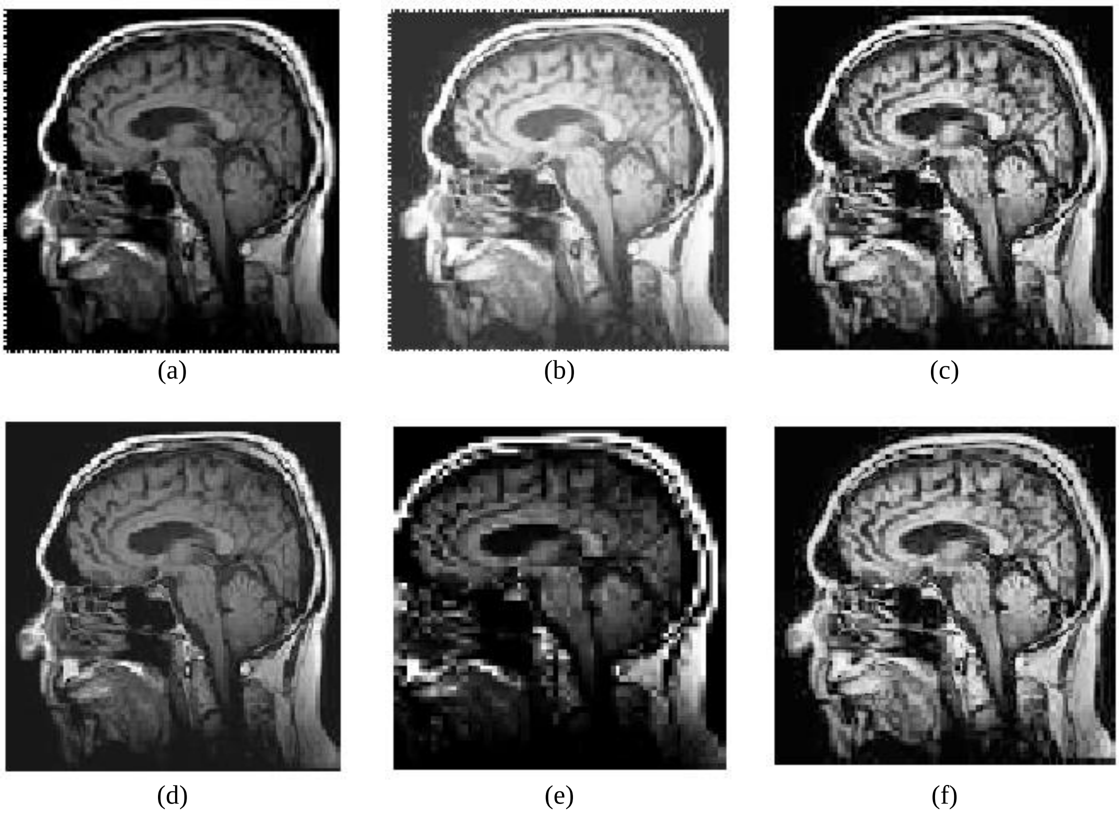


Figure 6. Simulation results using grey scale MRI image of a slice of a human head (a) original image, (b) HE method, (c) CLAHE method, (d) WT method, (e) fuzzy-based method, and (f) tri-modal method

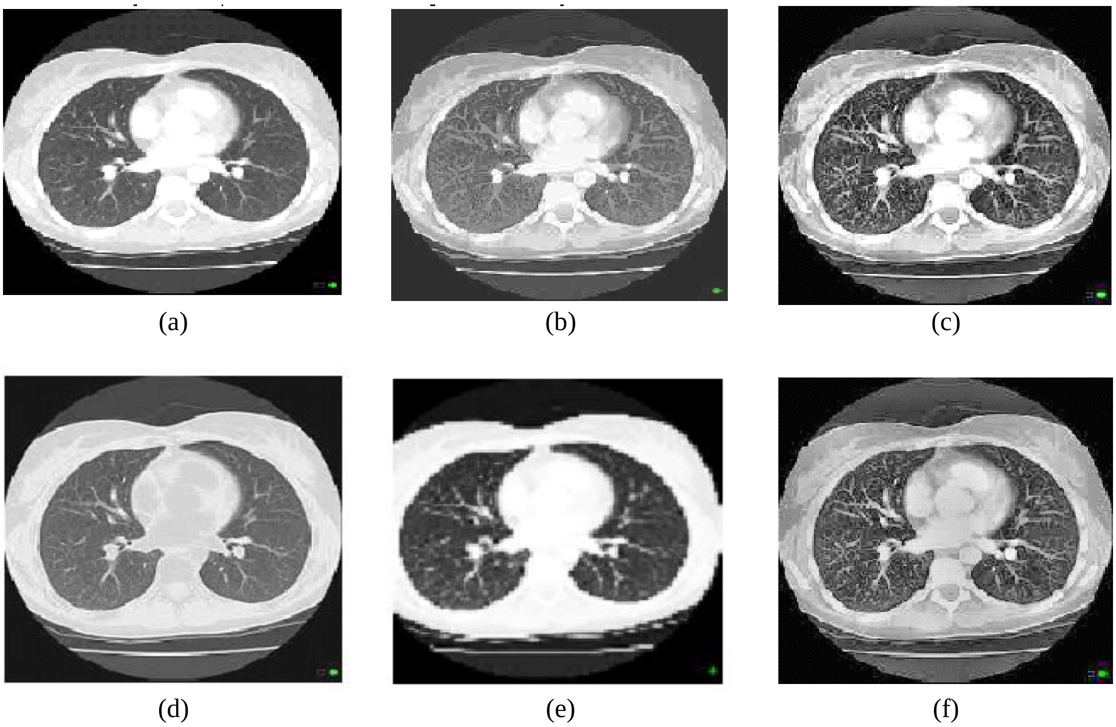


Figure 7. Simulation results using grey scale bright CT scan image of a human chest (a) original image, (b) HE method, (c) CLAHE method, (d) WT method, (e) fuzzy-based method, and (f) tri-modal method

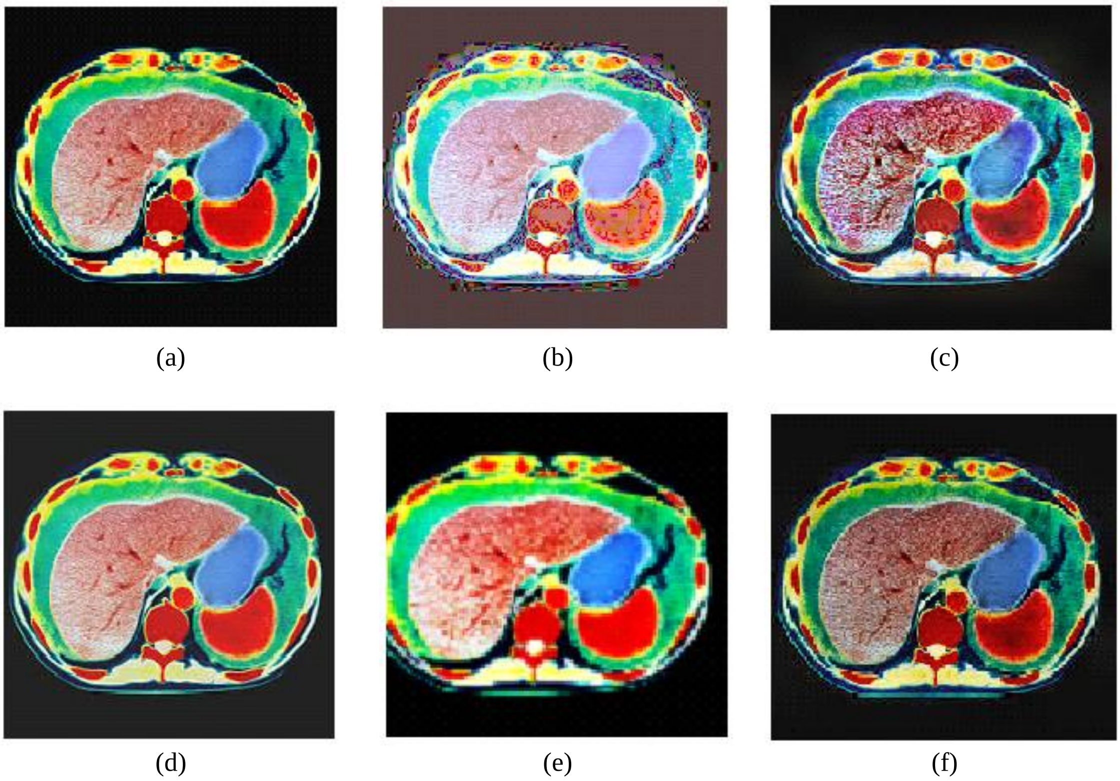


Figure 8. Simulation results using colored CT scan image of a human liver (a) original image, (b) HE method, (c) CLAHE method, (d) WT method, (e) fuzzy-based method, and (f) tri-modal method

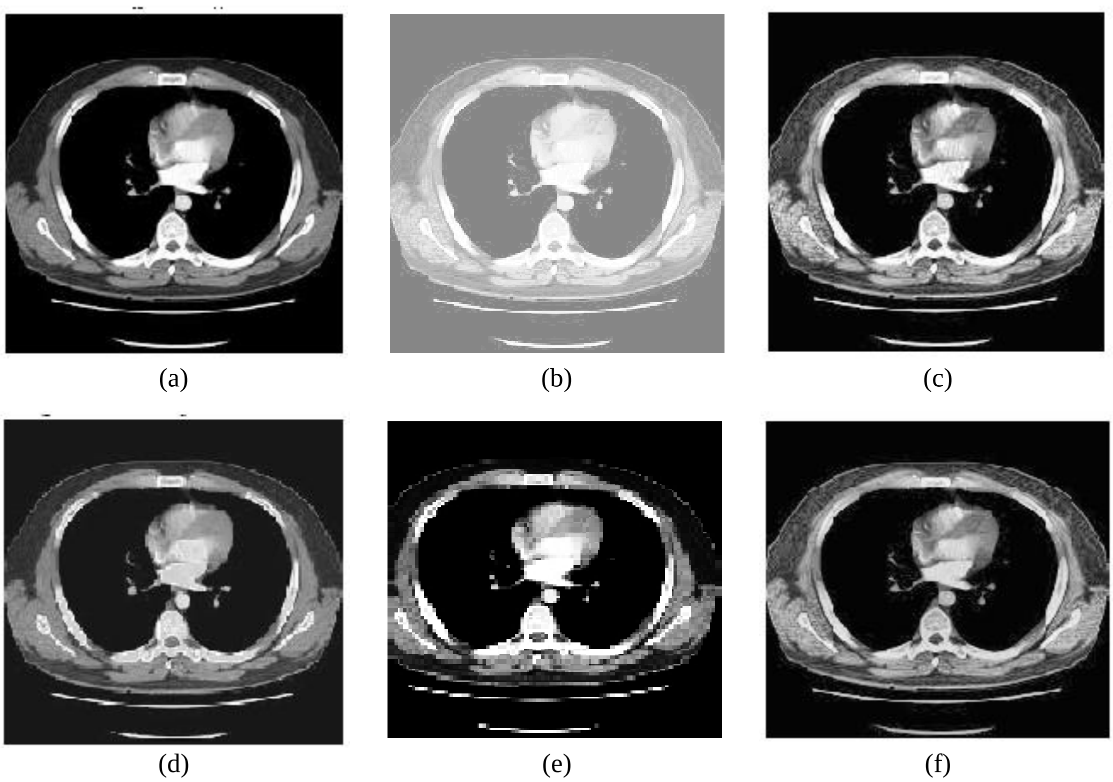


Figure 9. Simulation results using grey scale dark CT scan image of a human chest (a) original image, (b) HE method, (c) CLAHE method, (d) WT method, (e) fuzzy-based method, and (f) tri-modal method

Table 1. Results of subjective evaluation based on simulated outputs images

	HE	CLAHE	WT	Fuzzy-based	Tri-modal
X-ray 1	1	3	1	-	5
X-ray 2	-	2	3	-	5
X-ray 3	-	3	2	-	5
MRI 1	-	3	3	-	4
MRI 2	1	3	2	1	3
MRI 3	1	3	3	-	3
CT 1	2	4	-	-	4
CT 2	-	1	5	-	4
CT 3	-	2	2	3	3
Total opinion score	5	24	21	4	36
Percentage opinion score (%)	5.56	26.67	23.33	4.44	40.00

Results of subjective evaluation of the proposed tri-modal medical images enhancement method alongside HE, CLAHE, and WT fuzzy-based methods as presented in Table 1 show that HE, CLAHE, WT, fuzzy-based, tri-modal methods poll 5, 24, 21, 4, and 36, respectively, with a corresponding percentage score of 5.56, 26.67, 23.33, 4.44 and 40.00. Based on the opinion poll, outputs of the proposed tri-modal enhancement method are adjusted best out of the five methods with a percentage opinion score of 40%.

3.2. Results of quantitative evaluation

To further evaluate the performance of the proposed tri-modal medical image enhancement method in this work, its performance is evaluated quantitatively along with those of four other methods using those nine test images as well as those four other methods utilized in section 3.1. For ease of reference, the nine test images are denoted as a greyscale human leg (X-ray 1), great scale human hand (X-ray 2), a colored sliced human ankle (X-ray 3), colored sliced human head (MRI 1), greyscale human stomach (MRI 2), greyscale sliced human head (MRI 3), bright scan of the human chest (CT 1), colored scan of the human liver (CT 2), dark scan of the human chest (CT 3), respectively. Tables 2-4 show the results of evaluated parameters for X-ray, MRI, and CT images, respectively. It ought to be noted that an enhancement technique is adjudged better than others when the output image using the method has the lowest AMBE, highest PSNR, and highest entropy values when compared with outputs from other techniques.

Table 2. Results of evaluation using X-ray images

Parameters	HE	CLAHE	WT	Fuzzy-based	Tri-modal method
X-ray 1					
AMBE	30.3147	4.412	13.4788	5.0688	1.8723
PSNR (dB)	21.8869	25.7945	24.6418	24.0748	26.9598
Entropy	5.9535	7.6852	7.5499	6.9142	7.7506
Execution time(s)	0.6552	1.2100	8.1745	1.9968	1.2168
X-ray 2					
AMBE	176.4873	7.2237	17.7063	5.8612	5.7081
PSNR(dB)	21.8869	37.0348	37.8187	34.2607	37.8809
Entropy	2.4016	2.8113	2.5473	2.5142	2.9960
Execution time(s)	0.8580	1.4664	7.1760	2.5142	1.5600
X-ray 3					
AMBE	126.3081	10.6127	16.4454	4.7596	2.9192
PSNR(dB)	18.9992	32.3321	34.6365	33.3757	35.3658
Entropy	3.6124	4.5298	4.6992	4.1005	4.8869
Execution time(s)	0.6864	1.4196	3.1668	3.3852	0.9672

Table 3. Results of evaluation using MRI images

Parameters	HE	CLAHE	WT	Fuzzy-based	Tri-modal method
MRI 1					
AMBE	114.5826	8.9643	17.5420	3.0477	13.3308
PSNR (dB)	19.4901	30.8717	31.1114	29.8268	39.8003
Entropy	4.1516	4.8347	4.8408	3.9740	4.8542
Execution time(s)	0.7176	1.0296	6.5364	2.5740	1.1388
MRI 2					
AMBE	78.2697	41.8716	12.3570	9.6180	1.0920
PSNR(dB)	21.8028	25.9598	34.8351	31.2598	34.9661
Entropy	5.3440	7.2459	6.5817	6.2096	6.6250
Execution time(s)	0.6864	1.1700	2.0904	2.0748	1.0920
MRI 3					
AMBE	76.2243	33.5974	16.9594	7.8905	2.3034
PSNR(dB)	21.7453	26.2606	31.7403	34.3048	34.9056
Entropy	5.1789	6.9832	6.6454	6.0374	6.4281
Execution time(s)	0.7332	1.2324	2.106	2.056	1.1232

Table 4. Results of evaluation using CT images

Parameters	HE	CLAHE	WT	Fuzzy-based	Tri-modal method
CT 1					
AMBE	9.1537	8.3162	6.1802	0.5923	17.4357
PSNR (dB)	21.7734	22.8244	21.5409	20.1151	24.6593
Entropy	5.2634	7.0400	6.3604	6.0157	7.0439
Execution time(s)	0.7488	1.3416	5.8344	2.5896	1.2324
CT 2					
AMBE	50.9408	7.1412	14.5903	2.0132	11.9924
PSNR(dB)	22.0169	27.0662	26.7366	25.3900	31.2584
Entropy	4.7482	7.0844	6.0789	5.2845	6.4637
Execution time(s)	0.7176	1.1700	5.8188	2.5272	1.1388
CT 3					
AMBE	115.5068	11.3167	16.9070	1.2414	7.1730
PSNR(dB)	19.3431	30.3529	31.8267	31.5521	32.0760
Entropy	3.2856	4.7797	4.6187	4.6185	4.8931
Execution time(s)	0.7956	1.0140	6.0528	2.3712	1.2636

A cursory look at the results of objective parameters shown in Tables 2-4, is quite revealing. First, the PSNR figure return by the proposed tri-modal method is the highest in all nine test images. Second, the tri-modal method performs best with X-ray images in terms of AMBE, PSNR, and entropy figures in all three X-ray test images used. However, mixed results are recorded in the case of MRI and CT images. While the tri-modal method is best in terms of PSNR figure in all MRI images used, it is about 67% and 33% best in terms of AMBE and entropy, respectively. In CT images, the same trend is observed in values of PSNR as the tri-modal method outperforms other methods while it is generally not the best in terms of other parameters. As was the case with MRI, the tri-modal method is about 67% best in entropy and far less in terms of AMBE using CT images. It can be safely said that in terms of PSNR, the tri-modal method proposed in this paper is the priority.

In terms of execution time, the tri-modal technique compares favorably with those four other single-mode approaches. Although tri-modal is not the fastest in any of the experiments, it is, however, faster than some of the singular techniques as can be observed in the results of execution times for different methods. Judging by both evaluations involving X-ray, MRI, and CT images, the tri-modal method is fast enough and can be deployed for the enhancement of a wide range of medical images.

4. CONCLUSION

A tri-modal method for medical image enhancement has been proposed in this paper. The proposed algorithm is suitable for both grey and color image enhancement and does not require specification or adjustment of parameters for its operation. Simulation results show that the proposed enhancement method works well with a range of medical images (X-ray, MRI, and CT images) with a high PSNR figure and comparable execution time with previous enhancement methods that are based on histogram equalization, CLAHE, wavelet transform, and fuzzy logic.

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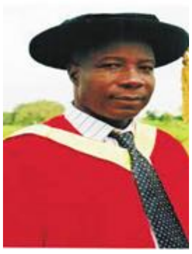

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