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Enhancing Radiological Imaging for Better Healthcare Outcomes Through High Performance Hybrid Approach

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Abstract

Radiological image enhancement algorithms provide a range of techniques to modify images, aiming for optimal visual quality. The selection of these techniques depends on the specific task, image content, observer characteristics, and viewing conditions. However, most enhancement methods for radiological images are tailored to specific applications, creating challenges in standardizing medical imaging practices and increasing costs due to varied enhancement protocols required by different imaging systems. To address this, a hybrid technique integrating unsharp masking, logarithm transformation, and adaptive histogram equalization has been developed. This hybrid method was evaluated against CLAHE and Wavelet Transform-based methods using radiological images. The results showed that the proposed hybrid method consistently achieved the lowest mean squared error (MSE), highest peak signal-to-noise ratio (PSNR), and highest average mean brightness error (AMBE), demonstrating its superior performance in enhancing radiological images. This innovative approach not only enhances diagnostic accuracy but also supports the sustainability of medical imaging infrastructure by streamlining enhancement protocols across diverse imaging systems.

Keywords: Medical, enhancement, un-sharp masking, log transformation, adaptive equalization

Introduction

Image enhancement is a fundamental image pre-processing technique in computer vision. It finds usefulness in applications such as: satellite imagery, medical imaging system, pattern recognition, feature extraction from images etc. Low quality and low contrast in images can be caused by several factors like low illumination in the camera's capturing area, poor resolution of the camera, operator's lack of knowledge of operating the camera and so on.

Many algorithms for contrast enhancement have been developed and are available in the literature. Such efforts include a perceptually motivated automatic colour contrast enhancement technique (Anustrup and Gerard, 2010), compressed domain contrast and brightness improvement algorithm for colour image (Prabukumar and Christopher, 2013), a hybrid image enhancement technique based on contrast stretching and peak based histogram equalization (Balachandra and Manjunath, 2012), wavelet-based contrast enhancement (Numan *et al.*, 2013), adaptive contrast enhancement of coloured foggy images (Mohanran *et al.,* 2014). The main drawback of most of these researches is that good quality images are produced at the expense of loss of information due to over enhancement. Also, the process execution time of most of these methods is longer than necessary.

Medical images are special in that they enable close look at the internal organs of the body without intrusion and are primarily used for diagnostic and therapeutic purposes. Consequent of this, a foray of techniques of obtaining images of internal human organs exist for medical imaging. Examples of such

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medical imaging types include Computed Tomography (CT), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), Magnetic Resonance Imaging (MRI), X-ray and Ultrasound. Operating principles of these techniques of medical imaging, in the production of images of internal human organs, are either based on reflection of propagating sound waves or electromagnetic waves (which can be in form of non – ionizing radio waves, calculated amount of ionizing electromagnetic waves or strong magnetic field). These non-intrusive modalities usually result in low quality images; thus, such images need enhancement to make the obscured details visible for accurate deployment for intended usage, which is diagnosis.

Several image enhancement methods have been developed over the years but they often fail in producing satisfactory images due to reasons that can be summed to over-enhancement which leads to loss of details (Kuldeep, et al., 2017). In addition, most of these enhancement techniques are application specific as a single method cannot be applied to all types of medical images. This constitutes a bottleneck to standardization of medical imaging system practices, leading to increase cost, as different medical imaging system requires different enhancement protocols.

It is therefore imperative to develop a method that can be applied for the enhancement of major medical images, if not all, at least radiological images, to produce the true state of the internal organs captured. This will go a long way of ensuring accurate diagnosis and therapy at a reduce cost. In addition, process execution time of most of previous developed methods is long than necessary. Thus, there is need for a method that produces fast and satisfactory results. These two needscombined together form the problem this research is embarked upon to address.

This research work proposes hybrid of three different techniques for the enhancement of radiological medical images. The first method is Un-sharp Masking (USM), which is to be used in sharpening the image via enhancement of the edges thereby removing blur that might be inherent in the input medical image. The obtained output from the processing of radiological image using USM will serve as the input to Logarithm Transformation (LT) which is aimed at increasing the brightness of dark pixels in the image to improve its dynamic range. LT is expected to bring out some of the hidden details. Lastly, the output of LT will serve as input to the AHE technique which is expected to improve the contrast. The output of AHE stage represents the final output of the proposed tri-modal radiological image enhancement scheme. The method in sequence is coined as USM-LT-AHE radiological images 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, among others.

Methods

Figure 1 illustrates the proposed hybrid enhancement method, USM-LT-AHE in block diagram. The research entails two image processing research areas namely, image de-blurring and contrast enhancement. The USM was adopted for image de-blurring (blur removal/sharpening) and contrast enhancement using log transformation while Adaptive histogram equalization was implemented on the already sharpened image. The proposed algorithm was implemented in MATLAB environment.

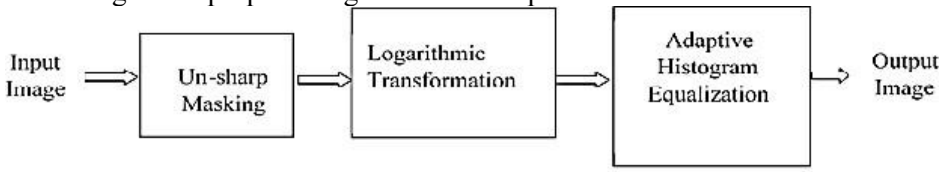


Figure 1: Block diagram of proposed algorithm

Un-sharp Masking

USM enhances small structures and bring 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 using Laplacian filter. The output of the Laplacian filter (blur copy of the original image) is subtracted from the original (input) image so as to restore the gray tones lost through the use of Laplacian (because the centre coefficient of Laplacian spatial mask is negative).
Mathematically, un-sharp masking image is generated using:

$$Z(n,m) = X_o(n,m) - X_b(n,m) \quad (1)$$

where

$Z(n, m)$ is the un-sharp masking image

$X_O(n, m)$ is the original image

$Xb(n, m)$ is the blurred copy from Laplacian filter (also known as correction signal).

Multiplication of (1) by a fractional value (K), and addition of the product to the original image yields an outputimage that is sharper and more detailed. The resultant output image is expressed as:

$$Y(n,m) = X_o(n,m) + KZ(n,m) \quad (2)$$

Where

$Y(n, m)$ is the output image, 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 0.7 (Naglae and Norio, 2006).

Logarithmic Transformation

Log transform algorithm that is used mapped a narrow range of low gray values to a wider range of gray levels. When applied to a digital image, it maps the dark intensity values to higher or brighter values, in order to make the details present more visible. In other words, by applying log transform on images, the lower pixels are mapped to a higher pixel and higher pixels are less affected. This algorithm resulted in a higher brightness and contrast of the output image. The output image from this algorithm is in the range of 0 - 1. To represent the values in the range of the input image, the transform will be multiplied by a scaling factor "C". The mathematicalimplication of the algorithm is as shown below.

$$S = C * \log(r+1) \quad (3)$$

where $C = maximum\ pixel\ value\ of\ input/\log(1 + \max pixel\ value\ of\ input)$; and r = input image

Histogram Equalization (HE)

Histogram of a digital image is the plot of n_k against k. For a digital image, its histogram can be represented mathematically as

$$h(r_k) = n_k h(r_k) = n_k \quad (4)$$

and x denoted the number of bits per pixel (class unit) of the image. For ths work, images of class unit 8 is used, hence,

$$L = 2^8 - 1 = 255 \quad (5)$$

This implies that the images that are used in this research have 256 intensity levels. For 8-bit pixels,the brightness ranges from zero (black) to 255 (white).

Normalizing the histogram will give probability density function which is obtained as

$$p(r_k) = \frac{n_k}{n} \quad (6)$$

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

Histogram equalization automatically determines a transformation function seeking to produce an output image with a uniform Histogram Equalization transformation can be denoted mathematically as

$$S_k = T(r_k) \quad (7)$$

where S_k is the cumulative density function, which is defined as

$$S_k = \sum_{j=1}^{k} p(r_l) \quad (8)$$

From (6) it can be inferred that

$$S_k = \sum_{j=1}^{k} \frac{n_j}{n} \quad \text{for k=1,2,3…L} \quad (9)$$

S_k is the intensity value of the output (proposed) image corresponding to the value of r_k in the input image. Using the transformation described above in (4) – (9), HE maps the input image into the entire range ($0, 1, \ldots, L$) by using $S_k$as a transfer function to produce an output image with a better contrast (Gonzalez and Woods, 1992).

Experiment

The implementation of the algorithm is done in MATLAB2018a environment on a 4GB, core i5 HP Elite book. Image processing toolbox functions such as imfilter, adapthisteq, rgb2hsv were utilized. Steps involved in the algorithm implementation are as described below:

(i) Load the biomedical image;
(ii) Determine if the image is colour or grey scale;
(iii) If the image is grey scale, read the values for each pixel;
(iv) If the image is colour, convert RGB colour space to HSV colour space and read the value component of the HSV;
(v) Apply LoG derived un-sharp masking on the output of step (iii) or (iv), as appropriate;
(vi) Apply a logarithmic mapping function to the output of step (v);
(vii) Apply AHE with clipping on the output of step (vi);
(viii) If the input image is grey scale, store the output of step (vii) and go to step (xi), else take the output of step (vii) as the new V (value) for the image;
(ix) Combine the input H and S components with the new V component obtained in step (viii) to get the new HSV for the image;
(x) Convert the new HSV colour space in step (ix) into to RGB colour space and store the output;
(xi) Output the enhanced image version of the original input image

The low-resolution test images were sourced from the Internet.

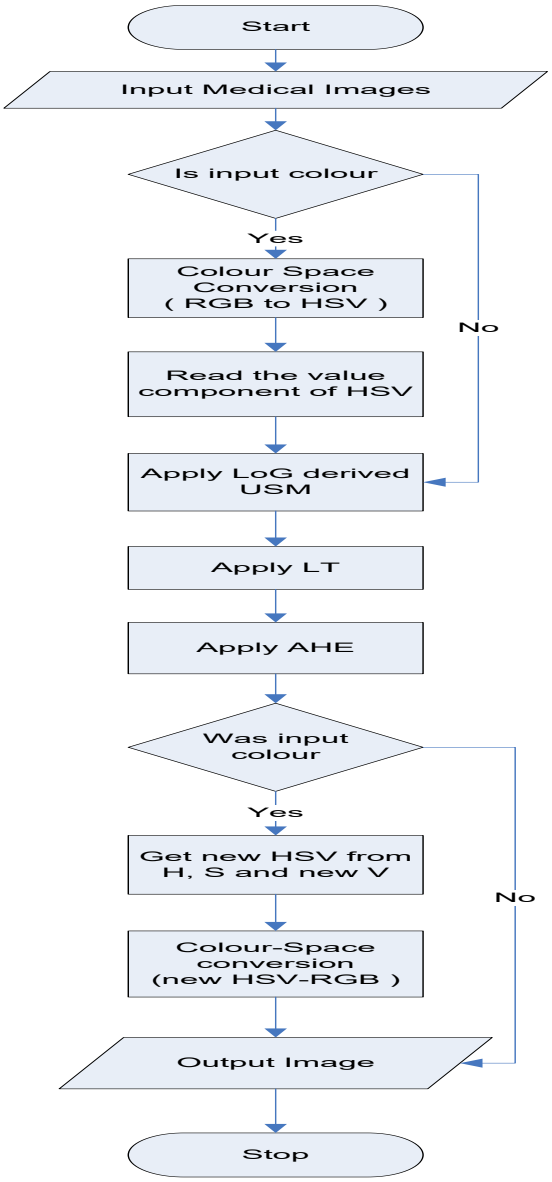


Fig. 2: Chart of the Hybrid Technique for Radiological Image Enhancement.

Six test radiological images are employed in the experiment: Coloured X-ray image of a slice of human ankle, Grey scale X- ray image of human hand, Coloured MRI image of a slice of human head, image of MRI scan of human stomach, Grey scale dark CT Scan image of a human chest and coloured CT scan of human liver.

Before going further, three standard performance indicators in image quality assessment that are popular in the image enhancement literature are employed for the qualitative evaluation of the developed USM-LT-AHE performance. These are:

i) Absolute Mean Brightness Error (AMBE),

$$AMBE = |E(y) - E(x)| \tag{10}$$

where $E(x)$ is the average intensity of input image; $E(y)$ is the average intensity of output image.

ii) Mean Squared Error (MSE)

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-i}\left[r(i,j) - r^{"}(i,j)^2\right] \quad (11)$$

where; $r(i,j)$ are image pixels of the input image and $r^{"}(i,j)^2$ are image pixels of the outputimage.

iii) Peak Signal-to-Noise ratio (The higher the PSNR, the better the method), Entropy (The higher theentropy, the better the method)

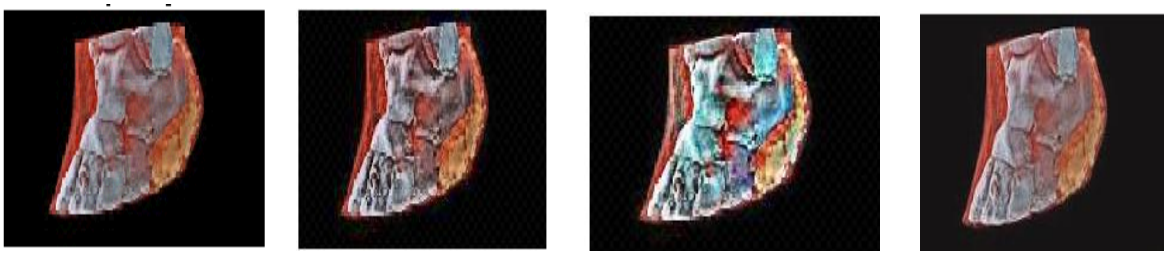
$$PSNR = 10\log_{10}\frac{R^2}{MSE} \quad (12)$$

In addition, the two other image performance of USM-LT-AHEis compared with those of enhancement methods available in the literature. Those methods are CLAHE, Wavelet Transform based methods.

Results

Qualitative Evaluation

Qualitative analyses are carried out using three different standard medical images (X-ray, MRI and CT scans) to give visual assessments of the developed hybrid USM-LT-AHE performances. Performance of USM-LT-AHE iscompared with those of CLAHE and fuzzy-based methods existing in the literature. Figures 3 – 8 illustrate obtained results when X-ray, CT-scan and MRI images considered as input, respectively.



a b c d

Fig. 3: Simulation results using grey scale Coloured X-ray image of human ankle (a) original image; (b) USM-LT-AHE method; (c) CLAHE method; (d) Wavelet Transform based method.



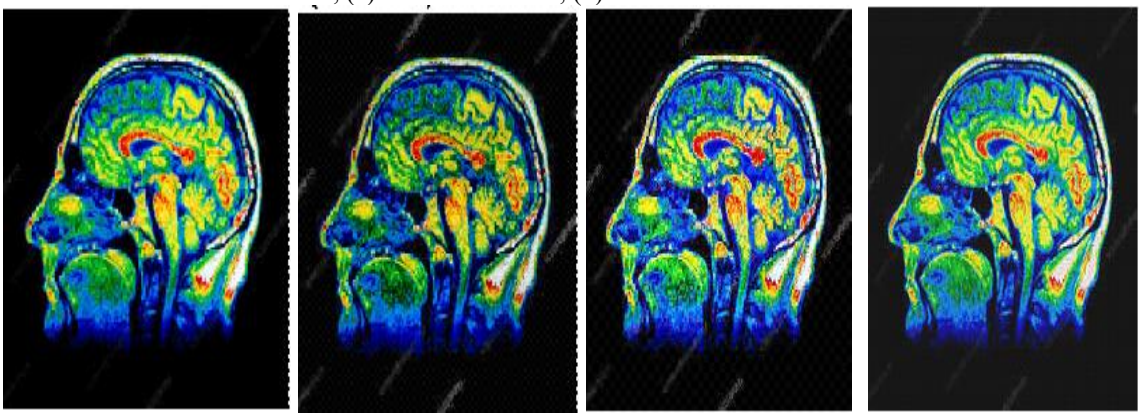
a b c d

Fig. 4: Simulation results using grey scale X-ray image of human hand (a) original image; (b) USM-LT-AHE method; (c) CLAHE method; (d) Wavelet Transform based method



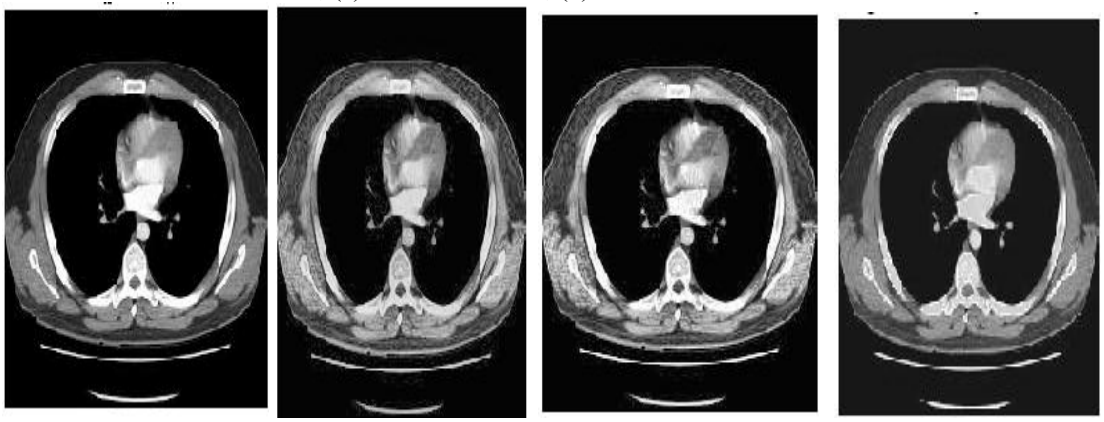
a b c d

Fig. 5: Simulation results using MRI image of a slice of human stomach (a) original image; (b) USM-LT-AHE method; (c) CLAHE method; (d) Wavelet – Transform based method



a b c d

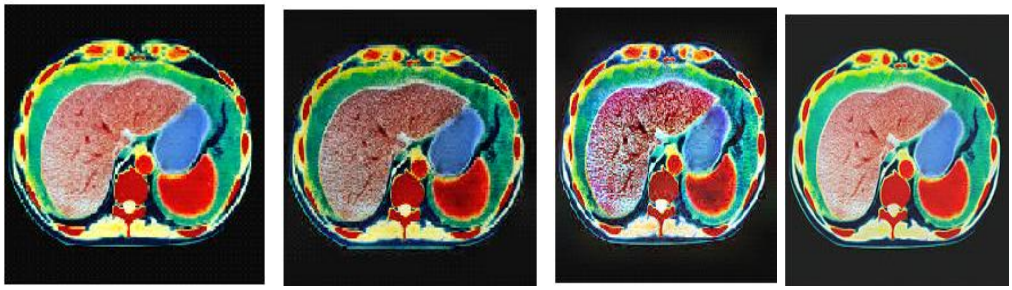
Fig. 6: Simulation results using Coloured MRI image of a slice of human head (a) original image; (b) USM-LT-AHE method; (c) CLAHE method; (d) Wavelet – Transform based method



a b c d

Fig. 7: Simulation results using Grey Scale dark CT scan image of a human Chest

(a) original image; (b) USM-LT-AHE method; (c) CLAHE method; (d) Wavelet Transform-based method



a b c d

Fig. 8: Simulation results using coloured CT scan image of a human liver

(a) original image; (b) USM-LT-AHE method; (c) CLAHE method; (d) Wavelet Transform-based method

Visual observation from the qualitative evaluation of our proposed USM-LT-AHE method and those of CLAHE and Wavelet Transform based methods illustrated in Figures 3 – 8 for X-ray, MRI and CT images, reveals that the performance of USM-LT-AHE surpasses those of CLAHE and Wavelet Transform based methods, especially for X-ray and MRI images.

To further ascertain the capability of the developed USM-LT-AHE for medical images enhancement, quantitative evaluation of the USM-LT-AHE is carried out using selected medical images earlier adopted for qualitative assessment. Four standard parameters for image enhancement were used and the results obtained are presented in Tables 1, 2, 3, 4, 5 and 6 for X-Ray, MRI and CT scan images, respectively

Table 1: Parameter-based evaluation using grey scale Coloured X-ray image of human ankle

Parameters	Methods		
	USM-LT-AHE	CLAHE	Wavelet Transform
AMBE	2.9192	10.6127	16.4454
MSE	0.02911	0.03942	0.03132
PSNR (dB)	35.3658	32.3321	34.6365
Entropy	4.8869	4.5298	4.6992
Execution time	0.9672	1.4196	3.1668

Table 2: Parameter-based evaluation using grey scale X-ray image of human hand

Parameters	Methods		
	USM-LT-AHE	CLAHE	Wavelet Transform
AMBE	5.7081	7.2237	17.7063
MSE	0.02264	0.02464	0.0228
PSNR(dB)	37.8809	37.0348	37.8187
Entropy	2.9960	2.8113	2.5473
Execution time	1.5600	1.4664	7.1760

Table 3: Parameter-based evaluation using MRI image of a slice of human stomach

Parameters	Methods		
	USM-LT-AHE	CLAHE	Wavelet Transform
AMBE	1.0920	41.8716	12.3570
MSE	0.0303	0.0746	0.0307
PSNR(dB)	34.9661	25.9598	34.8351
Entropy	6.6250	7.2459	6.5817
Execution time	1.0920	1.1700	2.0904

Table 4: Parameter-based evaluation using Coloured MRI image of a slice of human head

Parameters	Methods		
	USM-LT-AHE	CLAHE	Wavelet Transform
AMBE	13.3308	8.9643	17.5420
MSE	0.0187	0.0456	0.0446
PSNR(dB)	39.8003	30.8717	31.1114
Entropy	4.8542	4.8347	4.8408
Execution time	1.0296	1.1388	6.5364

Table 5: Parameter-based evaluation Grey Scale dark CT scan image of a human Chest

Parameters	Methods		
	USM-LT-AHE	CLAHE	Wavelet Transform
AMBE	7.1730	11.3167	16.9070
MSE	0.04232	0.0481	0.045
PSNR(dB)	32.0760	30.3529	31.8267
Entropy	4.8931	4.7797	4.6187
Execution time	1.2636	1.0140	6.0528

Table 6: Parameter-based evaluation Coloured CT scan image of a human liver

Parameters	Methods		
	USM-LT-AHE	CLAHE	Wavelet Transform
AMBE	11.9924	7.1412	14.5903
MSE	0.0439	0.06676	0.0690
PSNR (dB)	31.2584	27.0662	26.7366
Entropy	6.4637	7.0844	6.0789
Execution time	1.1388	1.1700	5.8188

Discussion

Checking the objective parameter tables, it could be deduced that the developed USM-LT-AHE algorithm performs better than CLAHE and Wavelet Transform based methods for the six images, going by values of MSE, PSNR AND Execution time. The lowest AMBE values indicate that the developed method produces images with good brightness preservation. Lowest MSE, highest Entropy and highest PSNR adds that the developed method enhanced the images without overdoing it with respect to the values of the pixels present in the original images. This implies that the USM-LT-AHE enhanced images guide against loss of information or details of the imputed images.

In all the six images, the USM-LT-AHE method has the lowest MSE, highest PSNR, fastest execution time and highest AMBE values indicating its ability to preserves the brightness best, except AMBE value for CT Scan image. The experimental results showed that USM-LT-AHE image enhancement method can successfully enhance grey scale and colour medical images as it neither loses useful information nor cause over-enhancement nor colour shift as seen mostly in CLAHE and Wavelet Transform based enhanced images.

Conclusion

A hybrid method for medical images enhancement was developed, the algorithm queries the input image to determine if it is grey scale or colour. If the input image is colour, the algorithm converts the RGB input image to HSV colour space. V-channel of HSV was enhanced while the S-channel and H-channel remained unchanged. The input grey scale or V-image was enhanced using unsharp masking technique followed by logarithmic transform and adaptive histogram equalization. The new gray scale image is the output image if the input image is grey scale. If the input image is colour, the algorithm combines the new V- image with the previous H and S- images that remained unchanged to produce the new HSV image. The new HSV is converted back to RGB to give the enhanced colour image.

The enhancement methodology developed does not require the user to specify or adjust parameters and

was shown to work well with a range of radiological medical images i.e. X-ray, MRI and CT images. The USM-LT-AHE method outperformed the Wavelet Transform based and CLAHE methods. It is also apparent that the images obtained with the USM-LT- AHE method are of better quality, compared to the Wavelet Transform and CLAHE methods tested. Specifically, the developed enhancement resulted in brighter details in low energy image regions and does not degrade the information in high energy image regions.

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