SCANNING VOL. 37, 116–125 (2015)

A New Algorithm for Improving the Low Contrast of Computed Tomography Images Using Tuned Brightness Controlled Single-Scale Retinex

Zohair Al-Ameen and Ghazali Sulong

UTM-IRDA Digital Media Centre (MaGIC-X), Department of Software Engineering, Faculty of Computing, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia

Summary: Contrast is a distinctive visual attribute that indicates the quality of an image. Computed Tomography (CT) images are often characterized as poor quality due to their low-contrast nature. Although many innovative ideas have been proposed to overcome this problem, the outcomes, especially in terms of accuracy, visual quality and speed, are falling short and there remains considerable room for improvement. Therefore, an improved version of the single-scale Retinex algorithm is proposed to enhance the contrast while preserving the standard brightness and natural appearance, with low implementation time and without accentuating the noise for CT images. The novelties of the proposed algorithm consist of tuning the standard single-scale Retinex, adding a normalized-ameliorated Sigmoid function and adapting some parameters to improve its enhancement ability. The proposed algorithm is tested with synthetically and naturally degraded low-contrast CT images, and its performance is also verified with contemporary enhancement techniques using two prevalent quality evaluation metrics—SSIM and UIQI. The results obtained from intensive experiments exhibited significant improvement not only in enhancing the contrast but also in increasing the visual quality of the processed images. Finally, the proposed low-complexity algorithm provided satisfactory results with no apparent errors and outperformed all the comparative methods. SCANNING 37:116–125, 2015. © 2015 Wiley Periodicals, Inc.

Key words: computed tomography, contrast enhancement, image processing, single-scale Retinex

Contract grant sponsor: The Universiti Teknologi Malaysia; Contract grant number: R.J130000.2528.03H70.

*Address for reprints: Zohair Al-Ameen, UTM-IRDA Digital Media Centre (MaGIC-X), Department of Software Engineering, Faculty of Computing, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia.
E-mail: qizohair3@live.utm.my

Received 17 November 2014; Accepted with revision 29 December 2014

DOI: 10.1002/sca.21187
Published online 6 February 2015 in Wiley Online Library (wileyonlinelibrary.com).

1. Introduction

In the digital imaging field, contrast enhancement is an important factor that enables an image to be clearly recognized by allowing a proper distinction of its details through a suitable contrast improvement to provide a better visual representation for the low-contrast images (Chang and Chang, 2010; Sen and Pal, 2011; Chouhan *et al.*, 2013). Moreover, the process of contrast enhancement is very similar to removing a layer of fog from such degraded images. In computed tomography (CT), acquired images are usually low-contrast (Tan *et al.*,2012; Zhang *et al.*, 2013), in which such degradation would severely corrupt the visual quality of the images making them difficult to interpret in clinical routines by reducing the lucidity of the image details and hindering the procedure for extracting valuable information. Various reasons lead to such degradation in CT images, including the use of improper image reconstruction algorithms (Bhadauria and Dewal, 2011), the occurrence of partial volume effects (PVE) phenomenon (Bhadauria *et al.*, 2011), image noise (Goliaei and Ghorshi 2011) and low radiation dose (Economopoulos *et al.*, 2010). In addition, many denoising methods reduce the image contrast, while attenuating its noise (Attivissimo *et al.*, 2010). The aforementioned reasons contributed significantly to the undesirable degradation of CT images. Thus, specialized methods must be used to attain results with better clarity. These methods are generally categorized as spatial and frequency domain methods (Poddar *et al.*,2013), in which the prevalent ones operate in the spatial domain. These methods involve histogram equalization (Celik, 2012), Sigmoid function

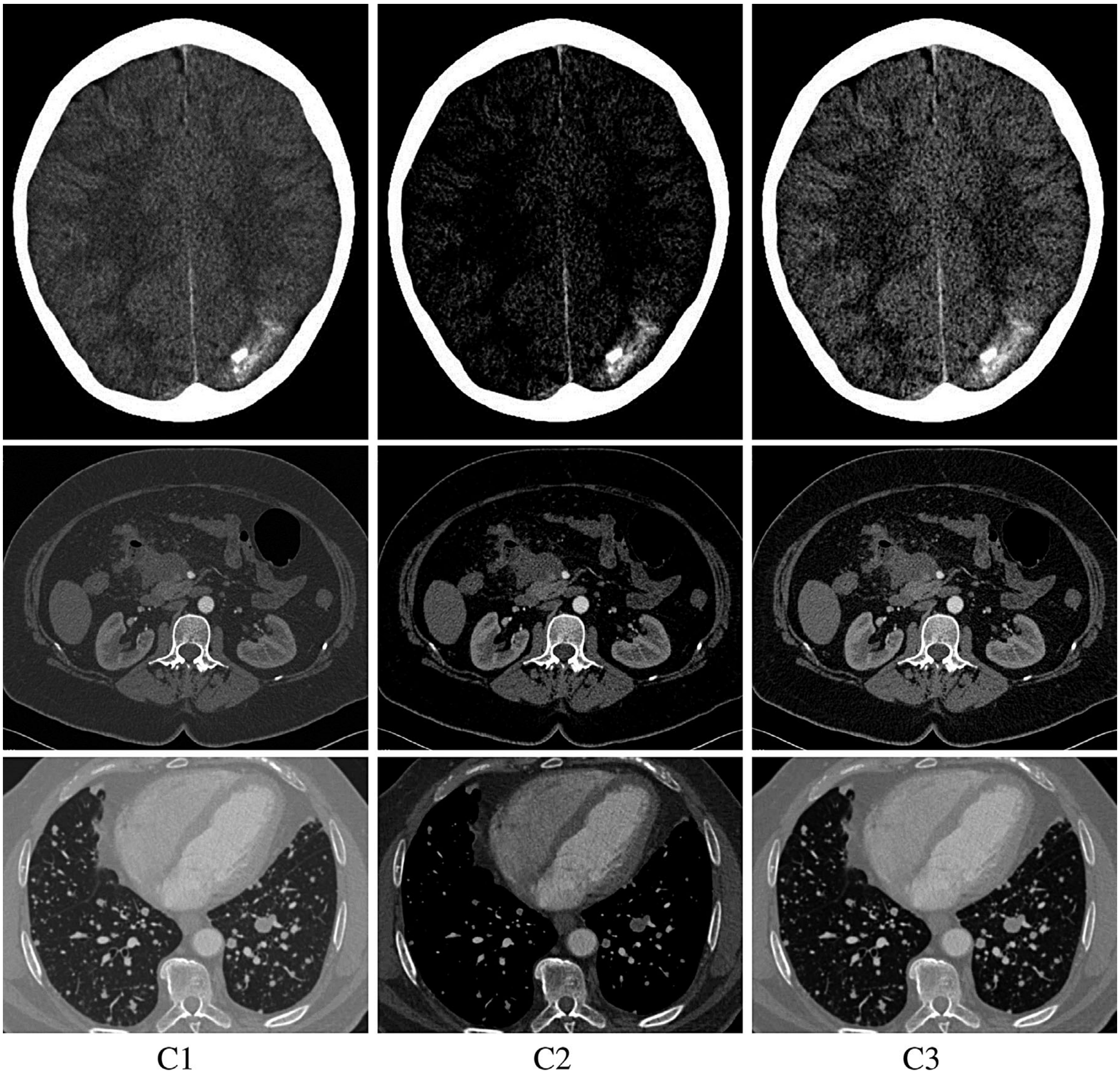

Fig 1. Columns from left to right: C1) naturally degraded low-contrast CT images; C2) enhanced by SSR; C3) enhanced by the proposed TBCSSR.

(Hassan and Akamatsu, 2004), low-pass, high-pass, homomorphic filters (Chouhan *et al*., 2013), normalization (Łoza *et al.,* 2013), log and power law transformations (Arun *et al.,* 2011; Tsai, 2013), contrast stretching (Yang, 2006) and the Retinex model (Chao *et al*., 2007). Lately, histogram based methods have received high consideration from scholars in the medical field, because they are fast and easy, and can be applied either locally or globally to an image. However, such methods have often failed to deliver satisfactory results for a wide selection of low-contrast images (Zeng *et al.,*2012) including CT images. It is important to highlight the recent studies that tried to improve the low-contrast of CT images. Georgieva (2010) used a gamma correction procedure to process a selected region of interest (ROI) of a given image, while Yousuf and Rakib (2011) proposed a global histogram equalization technique based on a probability function computed from a defined image ROI. Likewise, Ismail and Sim (2011) introduced a dynamic histogram equalization technique, which maintains the mean brightness of the inputted image to produce decent results, while Tan *et al.* (2012) proposed an extreme level eliminating adaptive histogram equalization technique, which implements locally on an image so that its output is adaptive to the local brightness. Moreover, Abdallah and Siddig (2013) employed a method that combines a local adaptive Gaussian scale mixture model with a median filter to exploit both clipped and nonlinear binning approaches, while Kandeel *et al.* (2014) have proposed a modified histogram based fast enhancement technique to process CT images. Although many innovative ideas have been proposed to overcome the low contrast problem, the outcomes, especially in terms of accuracy, visual quality and speed, are falling short and there remains considerable room for improvement. In this article, the focus is

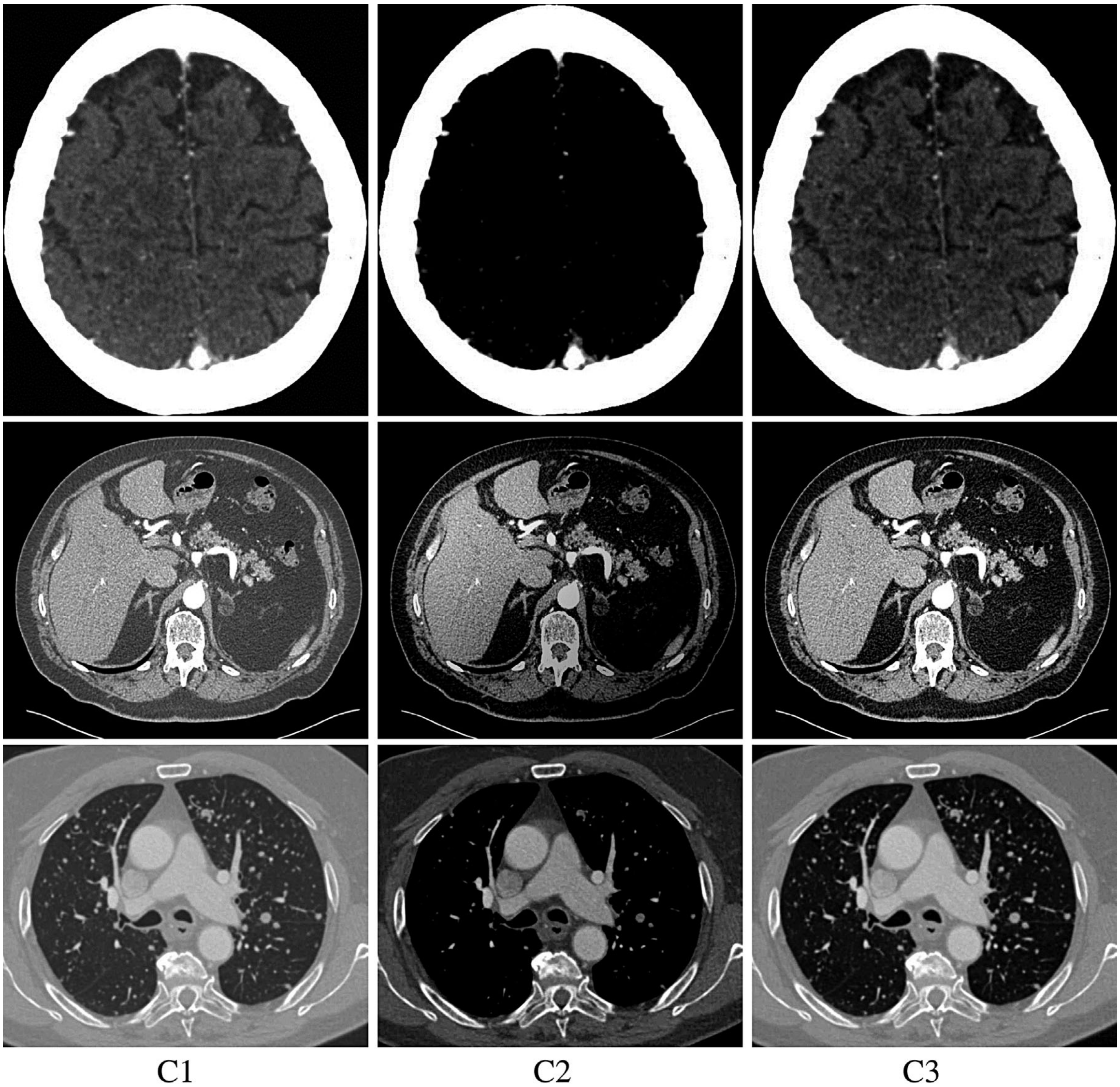

Fig 2. Columns from left to right: C1) naturally degraded low-contrast CT images; C2) enhanced by SSR; C3) enhanced by the proposed TBCSSR.

to propose a distinctive low-complexity algorithm that can enhance the image contrast while preserving its standard brightness and natural appearance with low implementation time and without accentuating the noise for CT images. It is important to perceive that preserving the natural appearance along with suitable contrast improvement is significant to avert the excess expansion of intensities and undesirable saturation. For this, many contrast enhancement methods have been investigated and the single-scale Retinex is selected because it has interesting latent abilities that can be developed and lead to imminent success with low-contrast CT images. The Single-Scale Retinex (SSR) is a recent contrast enhancement algorithm that is widely used by different imaging applications due to its easiness, effectiveness and rapidity. However, this algorithm has failed to process many CT images properly and produced unsatisfactory results, which suffered from unbalanced contrast and irregular brightness. Such degradation reduced the reliability of the standard SSR to be used as a trustworthy enhancement algorithm for clinical routines. Therefore, this study provides an improved SSR algorithm named as tuned brightness controlled single-scale Retinex, which can be used to process the low-contrast CT images efficiently and overcome the common problems of its standard version. The benefits of this algorithm include artifact-free results, fast implementation, low computation cost, acceptable visual quality and improves the contrast while preserving the standard brightness and natural appearance. The results obtained from extensive experiments on different images showed a considerable contrast enhancement in the processed images, wherein the obtained results appeared better than their initial versions. The rest of this article is organized as follows: In Section 2, the proposed algorithm is fully explained. In Section 3, the required empirical preparations, attained

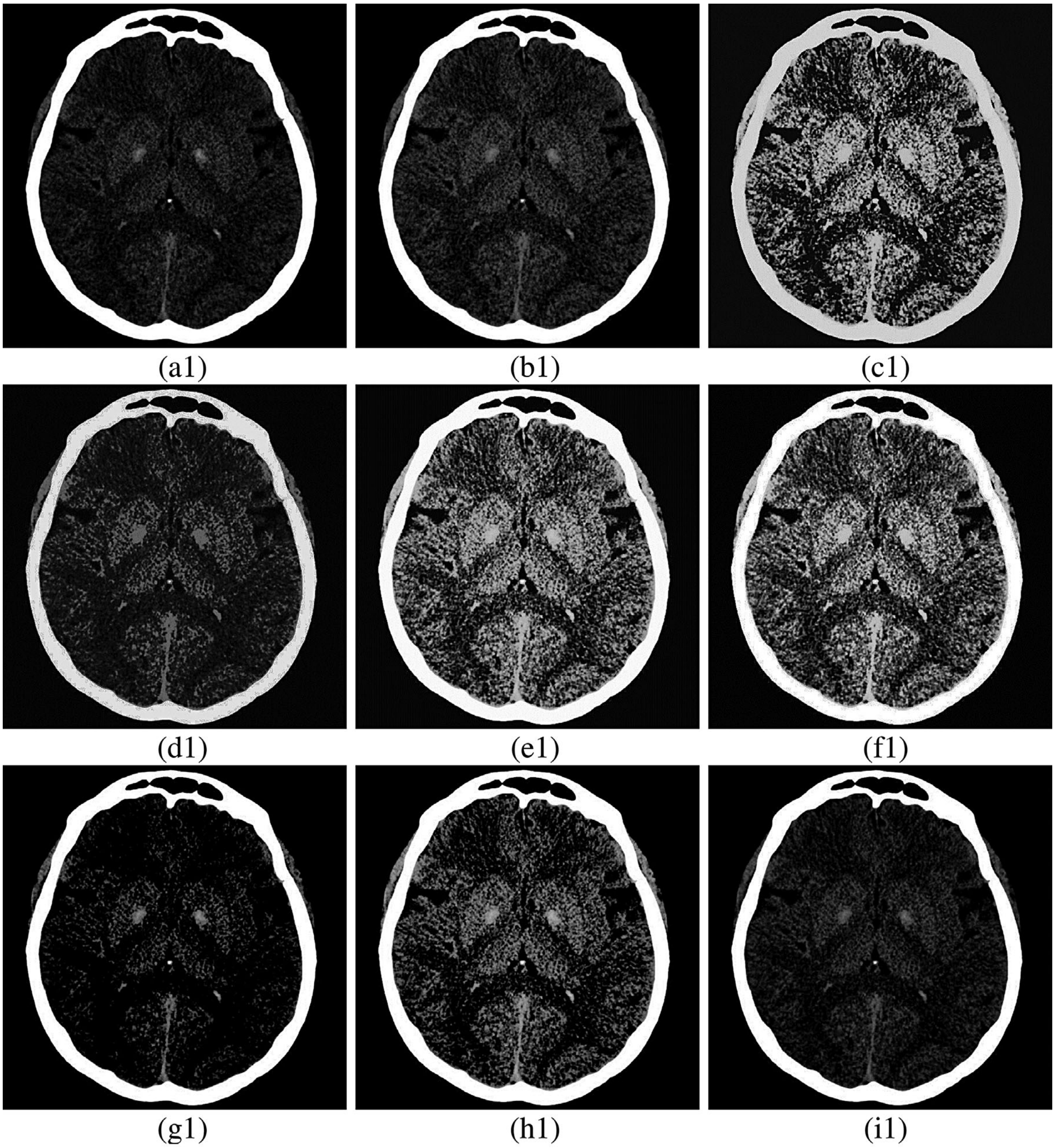

Fig 3. (a1) a true CT image; (b1) a degraded CT image (low contrast reduction); images enhanced by: (c1) RSIHE; (d1) BPDFHE; (e1) NMHE; (f1) ESIHE; (g1) SSR; (h1) TSSR; (i1) proposed (TBCSSR).

results and comparisons are presented along with their related discussions. In Section 4, the final concluding observations are delivered.

2. Proposed Tuned Brightness Controlled Single-Scale Retinex (TBCSSR)

While the Retinex theory (Land and McCann, 1971) was developed to describe the human vision perception, its derived versions have led to efficient methods in contrast enhancement (Beghdadi *et al*., 2013; Petro *et al*., 2014). One important derivation is the Single-Scale Retinex (SSR) (Jobson *et al*., 1997), which is a nonlinear contrast enhancement method that belongs to the class of center/surround functions where its output is calculated from the variance between the input (center) value and an average of its surroundings (Bogdanova, 2010; Meng *et al*., 2012). The basic principle of the SSR model is to estimate an illumination image by convolving the degraded image by a specific function, such as the Gaussian Surround Function (GSF). Then, compute the logarithms for both the degraded and the illumination images. Finally, subtract the second from the first to provide the enhanced result (Cheng *et al*., 2009). The standard SSR algorithm is determined as follows (Petro *et al*., 2014; Setty *et al*., 2014; Zhang and Duan, 2014):

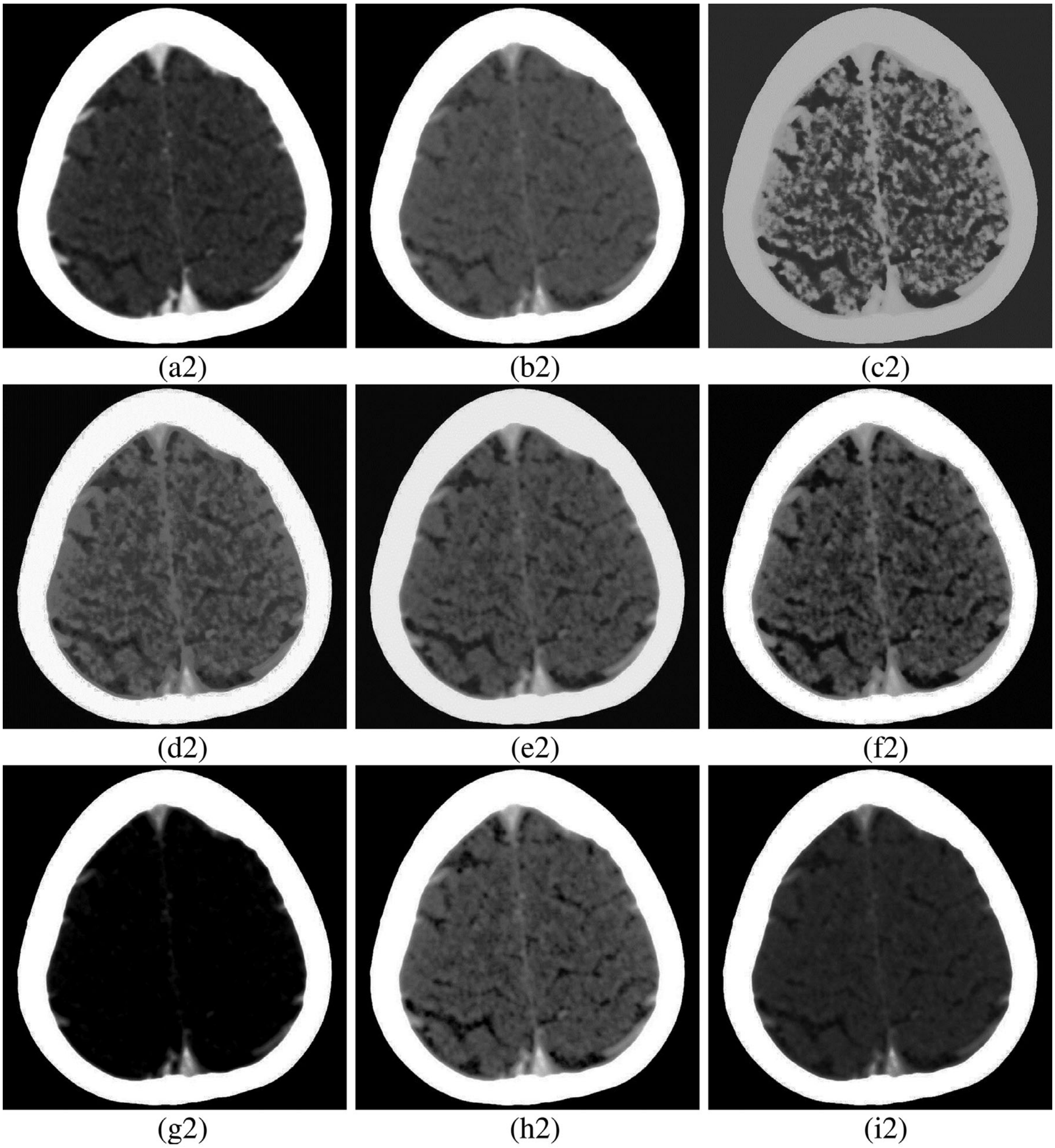

Fig 4. (a2) a true CT image; (b2) a degraded CT image (high contrast reduction); images enhanced by: (c2) RSIHE; (d2) BPDFHE; (e2) NMHE; (f2) ESIHE; (g2) SSR; (h2) TSSR; (i2) proposed (TBCSSR).

1- Compute a Gaussian Surround Function (GSF), which is given by:

$$G(x,y) = K \times e^{-\frac{(A^2+B^2)}{2\sigma^2}} \quad (1)$$

$$K = \frac{1}{\sum_{i=1}^{M}\sum_{j=1}^{N} e^{-\frac{(A^2+B^2)}{2\sigma^2}}} \quad (2)$$

Where, $G(x,y)$ is the GSF output, K is a normalization factor, x and y are the spatial coordinates, A and B are two arrays that the sizes of which are similar to the degraded image, wherein they represent the horizontal and vertical grayscale gradients, σ is a standard deviation constant which controls the amount of the retained spatial details and the image illumination, and $\times$ is an element-wise multiplication process.

2- Compute the Single-Scale Retinex (SSR) by the following formula:

$$O_{SSR}(x,y) = log[L(x,y)] - log[G(x,y) \otimes L(x,y)] \quad (3)$$

Where, $O_{SSR}(x, y)$ is the SSR output, $L(x, y)$ is the low-contrast image and $\otimes$ is a convolution process. The advantages of standard SSR include the low

TABLE 1 The recorded accuracy and time of the comparison.

#	Methods	Reduction	UIQI	SSIM	Time
1	*Low-contrast Images*	Low	0.8835	0.9451	—
		High	0.9178	0.9391	—
		Average	0.90065	0.9421	—
2	*RSIHE*	Low	0.2911	0.2863	0.115050
		High	0.5928	0.5048	0.168308
		Average	0.44195	0.39555	0.14168
3	*BPDFHE*	Low	0.5629	0.6111	0.053822
		High	0.7173	0.6675	0.049704
		Average	0.6401	0.6393	**0.05176**
4	*NMHE*	Low	0.2677	0.3469	0.111036
		High	0.6734	0.6944	0.274734
		Average	0.47055	0.52065	0.19289
5	*ESIHE*	Low	0.2899	0.4225	0.100746
		High	0.7107	0.7378	0.099336
		Average	0.5003	0.58015	0.10004
6	*SSR*	Low	0.7110	0.6594	0.117453
		High	0.5441	0.5615	0.121283
		Average	0.62755	0.61045	0.11937
7	*TSSR*	Low	0.8842	0.7654	0.147698
		High	0.9527	0.9507	0.148930
		Average	0.91845	0.85805	0.14831
8	*Proposed TBCSSR*	Low	0.9675	0.9711	0.164027
		High	0.9706	0.9551	0.179952
		Average	**0.96905**	**0.9631**	0.17199

Note: The bold values indicate the best achieved results.

computation cost, its effectiveness with many imaging applications and its fast implementation (Li, 2013). However, to determine its performance and filtering ability with CT images, the SSR was tested by applying it to more than 100 naturally degraded low-contrast images of different body parts. Moreover, the important observations that have been obtained from intensive tests can be summarized as follows: Firstly, the use of low σ value led to dark results with halo artifacts, while high values led to better illumination results. Secondly, the brightness and contrast for some images were improved properly, while for other images, they were worsened significantly. Thirdly, the standard SSR method delivered the worst results with lung CT images, in which many details of the filtered images became unnoticeable due to the presence of extra darkness. Therefore, the standard SSR algorithm is improved to avoid the aforesaid problems and make the SSR more adaptive to the contrast natures of CT images. The performance of the adjusted SSR, named as Tuned Single-Scale Retinex (TSSR), is improved experimentally by applying the following points: First, the value of 2σ is replaced by $M \times N$, which represents the image dimensions. This led to an increase in the algorithm's adaptivity and provided better illumination for the processed images. Moreover, a tuning parameter, β, is added to GSF, which has been experimentally proven to deliver better brightness and contrast. The modified GSF equations are given by:

$$G(x,y) = \frac{K \times e^{-\frac{(\mathrm{A}^2+\mathrm{B}^2)}{(M\times N)^2}}}{\beta} \tag{4}$$

$$K = \frac{1}{\sum_{i=1}^{M}\sum_{j=1}^{N} e^{-\frac{(\mathrm{A}^2+\mathrm{B}^2)}{(M\times N)^2}}} \tag{5}$$

Where, β is a tuning constant whose value fulfills $\beta > 0$. To this point, satisfactory results have been achieved, where the aforementioned problems of the standard SSR have been solved. However, another problem emerged, which is the extra brightness, wherein the results that fulfill $\beta \geq 2$ have excess brightness. The extra brightness is an undesirable event that must be processed correctly to produce natural appearance results. To overcome this event, an ameliorated sigmoid function is added to regulate the excessed brightness of the proposed TSSR, in which the proposed sigmoid function is implemented only when $\beta \geq 2$. The sigmoid is a nonlinear intensity enhancement function, which has been used in many imaging applications. The standard sigmoid function is described as follows (Kannan *et al.*, 2012):

$$f(g) = \frac{1}{1+e^{-\alpha(g)}} \tag{6}$$

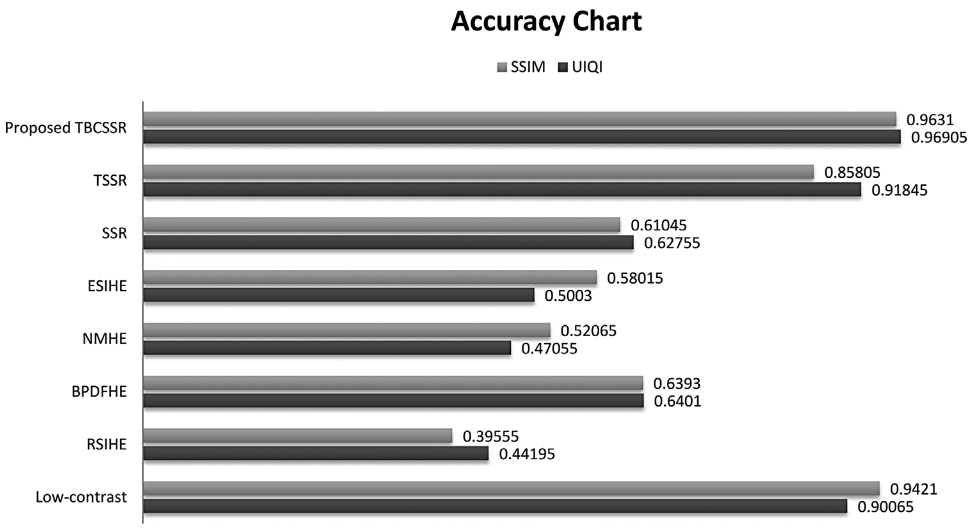

Fig 5. The graph of the average accuracy attained by UIQI and SSIM metrics.

Where, g is the degraded image and α is a constant parameter that controls the enhancement of the function. In this study, an ameliorated version of the latter function is used to provide better intensity results, which is described as:

$$f(g) = \frac{1}{1 + e^{-\alpha(g-\gamma)}} \tag{7}$$

Where, γ is an adjusting constant that by default, $\gamma = 2$. In this function, the α value is calculated automatically based on the value of β using the following formula:

$$\alpha = 1 + (\beta - T) \tag{8}$$

Where, T is a regulating value and by default, $T = 2$. By combining equation 7 and equation 8, the final ameliorated sigmoid function is expressed as:

$$s(g) = \frac{1}{1 + e^{-(1+(\beta-T))\times(g-\gamma)}} \tag{9}$$

Where, $s(g)$ is the contrast adjusted image. The above function produces good results with low dynamic range. Therefore, it is required to expand this dynamic range to fit its full natural interval. In the image processing context, the dynamic range expansion, which is also named normalization, is a procedure that alters the range of pixel intensity values. It is named normalization because it brings the image into a range that is more familiar to the senses (Boss *et al*., 2013). The following normalization formula is used to linearly scale pixels to fit its full natural range:

$$n(s) = \frac{[s(g) - \min(s(g))]}{[\max(s(g)) - \min(s(g))]} \tag{10}$$

Where, $n(s)$ represents the normalized image and the *min* and *max* operators are employed to get the maximum and minimum pixel values for a given image, respectively. The benefits of this algorithm include artifact-free results, fast implementation, low computation cost, acceptable visual quality and improves the contrast while preserving the standard brightness and

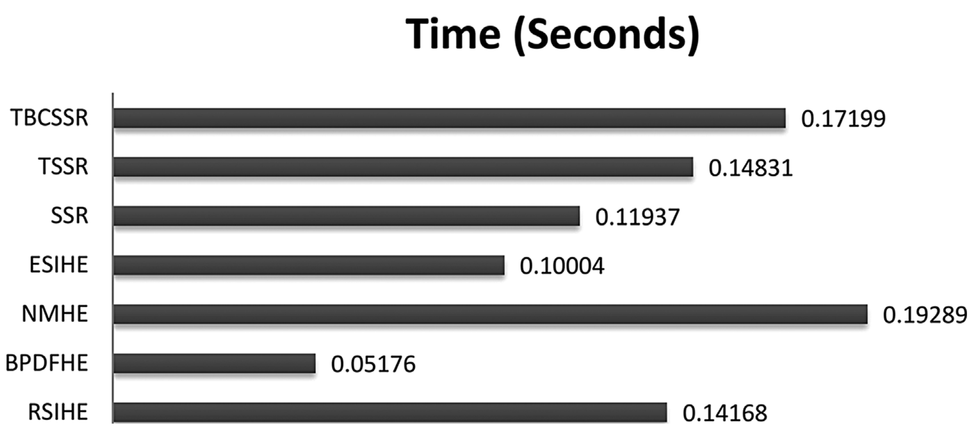

Fig 6. The graph of the average time spent by the comparative techniques.

natural appearance. As a final point, the subsequent pseudocode of Algorithm 1 is delivered to provide an accurate explanation about the execution specifics of the proposed algorithm.

Algorithm 1. The pseudocode of the proposed tuned brightness controlled single-scale Retinex algorithm

```
Input image L
Input parameter β
Set parameters T (default = 2), γ (default = 2)
Determine the image L dimensions to set M and N values
Compute the modified Gaussian surround function using equations (4), and (5), respectively
Compute the single-scale Retinex model using equation (3)
if β > 2 do
   Compute the ameliorated sigmoid function using equation (9)
   Normalize the resulted image using equation (10)
end if
Output the enhanced image
```

3. Results and Discussion

In this section, the required experimental arrangements are reported and the attained results are exhibited to prove the validity and the competence of the proposed algorithm in comparison with various contemporary contrast enhancement methods. In order to achieve robust and trustworthy experiments, two types of dataset are utilized, i.e. synthetic- and real-degraded images. The former are true images with reduced contrast while the latter are obtained from CT scans. The datasets images are obtained from different medical databases, such as ctisus.com, radpod.org, radiopaedia.org, commons.wikimedia.org and MedPix. In addition, different comparisons with the proposed algorithm are attained to evaluate its performance in terms of accuracy, visual quality and speed. In order to compare the clarity of the processed images against their original observations, the human vision is often used to assess the amount of contrast improvement. However, it is desired to utilize specific assessment metrics along with human vision. Hence, the authors investigated many image quality metrics and decided to use the Structural Similarity (SSIM) (Wang *et al.,* 2004), and Universal Image Quality Index (UIQI) (Wang and Bovik, 2002). The results of SSIM and UIQI are constant numbers that ranges between -1 and 1, where values near 1 indicate a high image quality and vice versa. If the two compared images are identical, the output of these metrics is 1. The proposed algorithm has been tested with many low contrast CT images for which some of the results are displayed in this article. To explore the filtering viability of the proposed algorithm against its original version, an experiment has been conducted using naturally low-contrast CT images, wherein the results are displayed in Figures 1 and 2. Moreover, comparisons have been achieved using synthetically contrast reduced images to evaluate the quality of the results using proper metrics. The contrast of the synthetic degraded images is reduced in a nonlinear fashion, because improving the contrast for CT images is achieved using nonlinear techniques (Lerman et al., 2006; Zhang *et al.*, 2008; Sajjadi *et al.*, 2012; Seeram, 2013). Afterwards, the contrast is improved by recursive sub-image histogram equalization (RSIHE) (Sim *et al.*, 2007), brightness preserving dynamic fuzzy histogram equalization (BPDFHE) (Sheet e*t al*., 2010), non-parametric modified histogram equalization (NMHE) (Poddar *et al*., 2013), exposure based sub image histogram equalization (ESIHE) (Singh and Kapoor, 2014), single-scale Retinex (SSR) (Jobson *et al*., 1997), proposed tuned single-scale Retinex (TSSR) and the proposed (TBCSSR) algorithm. The results of the comparisons are displayed in Figures 3 and 4. Table 1 reveals the recorded accuracy by SSIM, UIQI and the consumed time of the comparison. Figures 5 and 6 illustrate the graphs of the average SSIM, UIQI metrics and the consumed time respectively. Figures 1 and 2 contain three columns. The first column represents the naturally degraded low-contrast CT images. The second column represents the enhanced images enhanced images by SSR. The third column represents the proposed TBCSSR.

From Figures 1 and 2, the proposed algorithm performed well as the resulting images have a natural appearance with acceptable visual quality because the proposed algorithm enhanced the image contrast while preserving its brightness. Likewise, the images enhanced by SSR have an unrealistic appearance and in many cases, the results are worse than the original images.

Depending on the comparison results, the proposed algorithm performed the best in terms of quality metrics and visual quality as it produced the best accuracy values with an acceptable visual quality. Moreover, the images enhanced by TSSR have an imperfect contrast and somehow different to the original images. In addition, the SSR algorithm delivered a bad performance, because the resulting images were over-dark. Likewise, the RMSHE and BPDFHE techniques failed to process the low-contrast CT images, in which the results have a relatively unnatural contrast with visible errors. In addition, the NMHE and ESIHE techniques increased the brightness of the images while improving their contrast.

What is more, the proposed algorithm is also compared to other methods in terms of consumed time. As noted in Table 1 and Figure 6, the proposed algorithm needed a reasonable implementation time compared to the former comparable methods in that it took around 0.17 seconds to complete its task. As a final point, the performance of the proposed TBCSSR is very satisfying as the resulting images looked natural and have a realistic contrast, which is better than the other comparative methods.

4. Conclusion

A new algorithm for contrast enhancement is introduced in this study, which is suitable for low-contrast CT images. The novelties of the proposed algorithm consist of tuning the standard single-scale Retinex, adding a normalized-ameliorated Sigmoid function and adapting some parameters to improve its enhancement ability. The obtained results revealed that the proposed algorithm enhanced the images contrast while preserving their brightness. Thus, the processed images have a realistic appearance, natural contrast without producing the unwanted visible errors. The experimental results exhibited the favorability of the proposed TBCSSR algorithm in comparison to RSIHE, BPDFHE, NMHE ESIHE, SSR and TSSR using two sophisticated quality metrics, wherein the proposed algorithm gave the highest performance in terms of quality metrics and visual quality, as it delivered the best accuracy values with satisfactory quality results in moderate application time.

REFERENCES

Abdallah YMY, Siddig M. 2013. Contrast improvement of chest organs in computed tomography images using image processing technique. Asian J Med Radiol Res 1:39–44.

Arun R, Nair MS, Vrinthavani R, Tatavarti R. 2011. An alpha rooting based hybrid technique for image enhancement. Eng Lett 19:1–10.

Attivissimo F, Cavone G, Lanzolla AML, Spadavecchia M. 2010. A technique to improve the image quality in Computer Tomography. IEEE Trans Instrum Meas 59:1251–1257.

Beghdadi A, Larabi MC, Bouzerdoum A, Iftekharuddin KM. 2013. A survey of perceptual image processing methods. Signal Process-Image 28:811–831.

Bhadauria HS, Dewal ML. 2011. Performance evaluation of Curvelet and Wavelet based denoising methods on brain Computed Tomography images. IEEE International Conference on Emerging Trends in Electrical and Computer Technology.23–24 March Tamil Nadu. p 666–p 670.

Bhadauria HS, Dewal ML, Anand RS. 2011. Comparative analysis of curvelet based techniques for denoising of computed tomography images. IEEE International Conference on Devices and Communications.24–25 February. Mesra. p 1–p 5.

Bogdanova V. 2010. Image enhancement using Retinex algorithms and Epitomic representation. Cybern Inform Technol 3:10–19.

Boss R, Thangavel K, Daniel D. 2013. Automatic mammogram image breast region extraction and removal of pectoral muscle. Int J Sci Eng Res 4:1722–1729.

Celik T. 2012. Two-dimensional histogram equalization and contrast enhancement. Pattern Recogn 45:3810–3824.

Chang YC, Chang CM. 2010. A simple histogram modification scheme for contrast enhancement. IEEE Trans Consum Electr 56:737–742.

Chao WH, Cho CW, Shih YY, Chen YY, Chang C. 2007. Correction of inhomogeneous MR images using multiscale Retinex. Int J Image Process 1:1–16.

Cheng Y, Wang Y, Hu Y. 2009. Image enhancement algorithm based on Retinex for Small-bore steel tube butt weld's X-ray imaging. WSEAS Trans Math 8:279–288.

Chouhan R, Jha RK, Biswas PK. 2013. Enhancement of dark and low-contrast images using dynamic stochastic resonance. IET Image Process 7:174–184.

Economopoulos TL, Asvestas PA, Matsopoulos GK. 2010. Contrast enhancement of images using partitioned iterated function systems. Image Vision Comput 28:45–54.

Georgieva VM. 2010. An approach for computed tomography images enhancement. Electron Elec Eng Kaunas 2:71–74.

Goliaei S, Ghorshi S. 2011. Tomographical medical image reconstruction using Kalman filter technique. In Ninth IEEE International Symposium on Parallel and Distributed Processing with Applications Workshops. 26–28 May. Busan. p 61–p 65.

Hassan N, Akamatsu N. 2004. A new approach for contrast enhancement using sigmoid function. Int Arab J Inf Techn 1:221–225.

Jobson DJ, Rahman ZU, Woodell GA. 1997. Properties and performance of a center/surround retinex. IEEE Trans Image Process 6:451–462.

Kandeel AA, Abbas AM, Hadhoud MM, El-Saghir Z. 2014. A study of a modified histogram based fast enhancement algorithm (MHBFE). Signal Image Process Int J 5:55–67.

Kannan P, Deepa S, Ramakrishnan R. 2012. Contrast enhancement of sports images using two comparative approaches. Am J Intell Syst 2:141–147.

Land EH, McCann JJ. 1971. Lightness and retinex theory. J Opt Soc Am 61:1–11.

Lerman R, Raicu DS, Furst JD. 2006. Contrast enhancement of soft tissues in computed tomography images. In Proceeding of SPIE Medical Imaging 2006: Image Processing. 20 March. San Diego, Vol. 6144. p 2103–p 2110.

Li J. 2013. Application of image enhancement method for digital images based on Retinex theory. Optik 124:5986–5988.

Łoza A, Bull DR, Hill PR, Achim AM. 2013. Automatic contrast enhancement of low-light images based on local statistics of wavelet coefficients. Digit Signal Process 23:1856–1866.

Meng Q, Bian D, Guo M, Lu F, Liu D. 2012. Improved multi-scale retinex algorithm for medical image enhancement. In Information Engineering and Applications, 930-937. London: Springer.

Petro AB, Sbert C, Morel JM. 2014. Multiscale Retinex. Image Proc Line 4:71–88.

Poddar S, Tewary S, Sharma D, et al. 2013. Non-parametric modified histogram equalisation for contrast enhancement. IET Image Process 7:641–652.

Sajjadi M, Karami M, Amirfattahi R, et al. 2012. A promising method of enhancement for early detection of ischemic stroke. J Res Med Sci 17:843–849.

Seeram E. 2013. Computed tomography: physical principles, clinical applications, and quality control. UK: Elsevier.

Sen D, Pal SK. 2011. Automatic exact histogram specification for contrast enhancement and visual system based quantitative evaluation. IEEE Trans Image Process 20:1211–1220.

Setty S, Srinath NK, Hanumantharaju MG. 2014. An Improved Approach for Contrast Enhancement of Spinal Cord Images based on Multiscale Retinex Algorithm. Int J Imag Robot 12:112–125.

Sheet D, Garud H, Suveer A, Mahadevappa M, Chatterjee J. 2010. Brightness preserving dynamic fuzzy histogram equalization. IEEE Trans Consum Electr 56:2475–2480.

Sim KS, Tso CP, Tan YY. 2007. Recursive sub-image histogram equalization applied to gray scale images. Pattern Recogn Lett 28:1209–1221.

Singh K, Kapoor R. 2014. Image enhancement using Exposure based Sub Image Histogram Equalization. Pattern Recogn Lett 36:10–14.

Tan TL, Sim KS, Tso CP, Chong AK. 2012. Contrast enhancement of computed tomography images by adaptive histogram equalization-application for improved ischemic stroke detection. Int J Imag Syst Tech 22:153–160.

Tsai CM. 2013. Adaptive Local Power-Law Transformation for Color Image Enhancement. Appl Math Inform Sci 7:2019–2026.

Wang Z, Bovik AC. 2002. A universal image quality index. IEEE Signal Proc Let 9:81–84.

Wang Z, Bovik AC, Sheikh HR, Simoncelli EP. 2004. Image quality assessment: from error visibility to structural similarity. IEEE Trans Image Process 13:600–612.

Yang CC. 2006. Image enhancement by modified contrast-stretching manipulation. Opt Laser Technol 38:196–201.

Yousuf MA, Rakib MRH. 2011. An effective image contrast enhancement method using global histogram equalization. J Sci Res 3:43–50.

Zeng M, Li Y, Meng Q, Yang T, Liu J. 2012. Improving histogram-based image contrast enhancement using gray-level information histogram with application to X-ray images. Optik 123:511–520.

Zhang G, Sun D, Yan P, Zhao H, Li Z. 2008. A LDCT image contrast enhancement algorithm based on single-scale retinex theory. In International Conference on Computational Intelligence for Modelling Control & Automation.10–12 Dec. Vienna. p 1282–p 1287.

Zhang Q, Duan H. 2014. Biological weight selection of multi-scale retinex via artificial bee colony algorithm. Optik 125:1434–1438.

Zhang W, Liu J, Yao J, et al. 2013. Mesenteric Vasculature-guided small bowel segmentation on 3-D CT. IEEE Trans Med Imaging 32:2006–2021.