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CT scan contrast enhancement using singular value decomposition and adaptive gamma correction

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Abstract

We propose in this paper a new enhancement algorithm dedicated to dark computed tomography (CT) scan based on discrete wavelet transform with singular value decomposition (DWT–SVD) followed by adaptive gamma correction (AGC). Discrete wavelet transform (DWT) is considered to decompose the input dark CT image in four sub-bands. Singular value decomposition (SVD) is used in order to compute the corresponding singular value matrix of low–low (LL) sub-band image. The enhanced LL sub-band is determined by scaling the singular value matrix of original LL sub-band by an adequate correction factor, followed by inverse SVD. For a further contrast improvement, the new enhanced LL sub-band image is processed using an AGC algorithm. Finally, the obtained LL sub-band image undergoes inverse DWT together with the unprocessed sub-bands to generate the final enhanced image. This proposed method has the advantage of being fully automatic and could be applied for dark input images with either low or moderate contrast. Different dark CT images are considered to compare the performance of our proposed method to three other enhancement techniques using both objective and subjective assessments. Simulation results show that our proposed algorithm consistently produces good contrast enhancement, with best brightness and edges details conservation and with minimum added distortions to the enhanced CT images.

Keywords Dark CT scan · Contrast enhancement · SVD · AGC

1 Introduction

Different medical imaging modalities like computed tomography and magnetic resonance imaging are nowadays available. CT imaging is widely used for providing detailed morphological reconstructions of tissues and organs and therefore helping clinicians in diagnosis. In fact, in some cases, it is possible to visualize different tissues using CT imaging. However, for some other cases, it is difficult to identify the interface between two adjacent tissues (between liver and tumor tissues for example) or soft tissues (clot for example) in contact with physiological fluids [1]. Consequently,

when CT imaging is used, contrast imaging agents are frequently considered to better show the tissue of interest and display the presence of disease or injury. Nevertheless, contrast imaging agents are sometimes hurtful or even deadly for some patients due to the occurrence of anaphylaxis [2]. To avoid the use of contrast imaging agents, low-contrast CT images could be processed using an adequate contrast enhancement algorithm. The main goal in this case is to enhance the contrast of considered medical image and simultaneously preserve its edge information [3]. Indeed, small degradations of edge information degrade the quality of the image and could distort the clinician's interpretation.

Different methods are proposed in the literature to enhance the contrast and brightness of damaged images [4,5]. The global histogram equalization (GHE) method is a simple and effective method widely considered to enhance the image's contrast. The main idea behind using GHE is to transform the histogram of the input image by spreading and stretching its dynamics range to reach an overall contrast enhancement. In fact, the whole image is divided into equidistant levels defining different limits. These limits are recursively updated by introducing new limits between the

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old ones [6]. The overall contrast of the input image could be more efficiently enhanced using local histogram equalization (LHE) algorithm, but it presents the main drawback of higher computational complexity since it is based on using of fully overlapped sub-blocks [7,8]. Some more robust contrast enhancement algorithms using HE are proposed in the literature [9,10] like brightness preserving bihistogram equalization (BBHE), dualistic sub-image histogram equalization (DSIHE) [11] and brightness preserving dynamic histogram equalization (BPDHE) [12,13]. The main idea of these mentioned algorithms is to decompose the histogram of the input image into two sub-histograms according to a specific calculated threshold and therefore to process each sub-histogram individually. For BBHE, the threshold is calculated based on the intensity of the input image. For DSIHE, the threshold is calculated based on the median intensity value of the input image. For BPDHE, the threshold is computed according to the local maximum of the smoothed histogram.

HE-based contrast enhancement algorithm is considered by different researchers in order to improve the contrast of medical image. Sundram et al. used a LHE method to enhance the contrast of mammogram image. This technique is able to improve the contrast of considered images and simultaneously conserve its local information [14]. Al-Juboori presented another technique to enhance the contrast of mammographic image. This algorithm combined both contrast limited adaptive histogram equalization and retinex techniques [15]. Ganesan et al. presented a seed-dependent adaptive region growing approach for contrast enhancement of CT images [16]. Yang et al. presented a contrast enhancement algorithm dedicated to medical images. This algorithm used both wavelet and Haar transforms for image decomposition and soft thresholding and nonlinear histogram equalization methods for contrast enhancement [17]. Kaur and Singh proposed an adaptive histogram equalization algorithm for contrast improvement of medical cephalometric images. This enhancement algorithm used biorthogonal spline wavelets in order to detect the edge pixels and discard the pixels in homogeneous regions during image histograms computing process [18]. Wang and Shi presented a contrast enhancement algorithm based on DWT which simultaneously accomplishes the exact histogram specification and good image enhancement performance [19].

Although these adaptive and improved contrast enhancement methods are visually more pleasing than classical HE, they are not able to adjust the level of enhancement. In order to surmount the limits of HE methods, different researchers considered SVD technique for low- contrast image enhancement [20,21]. Two main categories of SVD-based contrast enhancement algorithms are proposed. For the first category, SVD is used on the pixel domain like singular value equalization algorithm [21]. Indeed, the singular value matrix,

obtained by SVD includes the illumination information of a considered image. The contrast enhancement based on the singular value equalization method processes this singular matrix, and other information will be conserved as same as before. For the second category, SVD is used on the frequency domain of an image. In this case, low-contrast image is processed using DWT [22] or discrete cosine transform (DCT) [23] followed by SVD, conducting, respectively, to DWT–SVD and DCT–SVD enhancement algorithms.

For DWT–SVD algorithm, the input image is processed using DWT in order to be decomposed into four frequency sub-bands: low–low (LL), low–high (LH), high–low (HL) and high–high (HH) sub-bands. In order to preserve the edge information (corresponding to the high frequency details) of the input low-contrast image from possible degradation, SVD technique is therefore applied only on the LL sub-band [23]. The same processing is considered for DCT–SVD algorithm except that the low sub-band image is obtained using DCT [20,23]. A new LL sub-band is determined by multiplying the obtained singular value matrix by a correction factor. The enhanced output image is generated using the inverse discrete wavelet transform (IDWT). The performances of DWT–SVD method are evaluated and compared to GHE, BPDHE, and SVD contrast enhancement algorithms, and simulation results indicated better performances for DWT–SVD over the others. Atta and Abdel-Kader presented an improved DWT–SVD method for contrast enhancement [24] where the enhanced singular value matrix is computed using the singular matrices of both input image and processed image using GHE. As mentioned above, the SVD-based methods enhance the low-contrast images by scaling its singular value matrix. Although these techniques may preserve the mean brightness better than HE techniques, they may be unsuccessful in achieving a better contrast enhancement.

Some other methods based on classically traditional gamma correction are also proposed. Gamma correction factor is set manually for such algorithm, but they did not give an appropriate enhancement for different types of images [25]. Bhandari et al. presented a simple method to improve the contrast of dark image based on knee function and gamma correction using DWT–SVD [26]. Frosio proposed a contrast enhancement algorithm of cephalometric radiographs based on gamma correction and soft tissue filter using histogram clustering [27]. Adaptive gamma correction algorithms are also proposed, and the gamma correction factor is computed for each input image according to its characteristics. Huang et al. presented a transformation technique that enhances the brightness of low-contrast images using adaptive gamma correction and probability distribution of luminance pixels [28]. Somasundaram and Kalavathi proposed an AGC method for contrast enhancement of medical image [29]. The gamma correction factor is estimated according to the cumulative histogram. Tiwari and Gupta presented an efficient method

to enhance the contrast of medical images based on gamma correction and homomorphic filtering [13]. Rahman et al. proposed an AGC algorithm to enhance the low-contrast satellite image. The parameters of gamma correction are adaptively calculated according to the statistical mean and standard deviation of the respective image [30].

In this paper, we propose a new approach to enhance the dark CT image using DWT–SVD technique followed by AGC algorithm. A great type of dark images collected from different body sites and using different equipments could be processed and improved using our proposed enhancement algorithm. In effect, we decompose in a first step the input image into four sub-band images using DWT. Only the LL sub-band is therefore processed by SVD technique in order to enhance its contrast. The contrast of obtained LL sub-band cannot conduct to the desired dynamic range expansion, and consequently, a poor contrast enhancement is observed. That is why the obtained LL sub-band image is processed in a second step using AGC transformation. The gamma correction factor is automatically computed for each input image according to its statistical information. Our proposed method gives better compromise between contrast improvement and edge conservation than DWT–SVD or AGC algorithms considered separately.

The rest of this paper is organized as follows: The principle of gamma correction technique is detailed in Sect. 2. Section 3 discusses the proposed AGC algorithm using DWT–SVD technique. Finally, simulation results and conclusion are, respectively, given in Sects. 4 and 5.

2 Gamma correction transformation

The gamma correction transformation is given as [25].

$$I_{\text{out}} = c \cdot I_{\text{in}}^{\gamma} \tag{1}$$

where I_{in} and I_{out} represent, respectively, the input and output image intensities. Both c and γ parameters are used to adjust the shape of the transformation function. In effect, a set of parameters (γ, c) could produce high performances for some considered images but not for some others [28]. In order to overcome this problem, Rahman et al. proposed a new method where γ and c parameters are determined dynamically and automatically for each input image according to its statistical characteristics [30]. Indeed, authors proposed to classify an original dark image I into either low-contrast class C_1 or moderate-contrast class C_2 according to the contrast of considered image using Eq. (2).

$$g(I) = \begin{cases} C_1 & \text{if } D \le 1/\tau \\ C_2 & \text{otherwise} \end{cases} \tag{2}$$

where $D = \text{diff}((\mu + 2\sigma), (\mu - 2\sigma))$ and τ is a constant considered to define the contrast of an input image. Experiments showed that $\tau = 3$ is an optimal choice to characterize the contrasts of different images. The standard deviation and the mean of the considered image intensity are, respectively, denoted by σ and μ [30]. According to Eq. (2), we classify an image as a low-contrast (class C_1) if $4\sigma \le 1/\tau$, meaning that the major pixel intensities of considered image are grouped within a small range. Otherwise, the image is classified as moderate contrast (class C_2).

2.1 Dark images with low-contrast

The majority intensities of a dark input image from the first class are grouped in a small range of dark gray levels around the mean intensity of the considered image. In order to improve the contrast of like input image, the transformation curve requires to flaunt the dark intensities to the higher intensities. Therefore, the main constraint in this case is to generate a transformation function that lies above the line $I_{\text{out}} = I_{\text{in}}$. As a response to this constraint, Rahman et al. showed that the value of γ could be calculated using Eq. (3) [30].

$$\gamma = -\log_2(\sigma) \tag{3}$$

The parameter c is also dynamically computed for different images according to Eq. (4).

$$c = \frac{1}{1 + \text{Heaviside}(0.5 - \mu) \cdot (k - 1)} \tag{4}$$

where k is determined using Eq. (5).

$$k = I_{\text{in}}^{\gamma} + (1 - I_{\text{in}}^{\gamma}) \cdot \mu^{\gamma} \tag{5}$$

and the Heaviside function is defined as given by Eq. (6) [31].

$$\text{Heaviside}(x) = \begin{cases} 0, & \text{if } x \le 0 \\ 1, & \text{if } x > 0 \end{cases} \tag{6}$$

The output image I_{out} is determined using Eq. (1). Figure 1a shows that the transformation curves of low-contrast dark images for different values of μ and σ fall effectively above the line $I_{\text{out}} = I_{\text{in}}$. Additionally, the obtained curves are more steepness for the lower contrast, as desired. Figure 1b displays the original low-contrast dark image ($\mu = 0.0528$ and $\sigma = 0.0434$), the enhanced image using AGC algorithm ($\gamma = 4.5267$) and their respective histograms.
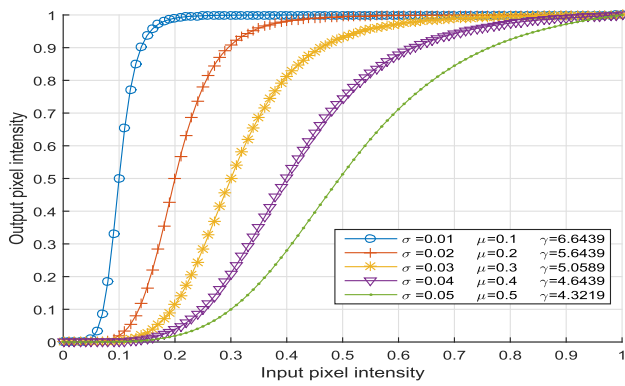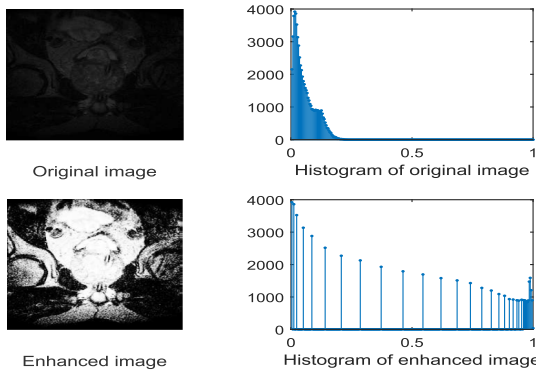
Fig. 1 Gamma correction for low contrast image: **a** Transformation curves for different values of μ and σ, **b** Original and enhanced images and their corresponding histograms

## 2.2 Dark images with moderate contrast

The intensities of a dark input image from the second class are scattered over the available dynamic range. In this case, I_{out} and c are calculated similarly using Eqs. (1) and (4). However, the correction factor γ is expressed differently using Eq. (7), not to make much stretching of the contrast [30].

$$\gamma = \exp\left[\frac{(1 - (\mu + \sigma))}{2}\right] \tag{7}$$

Figure 2a illustrates the transformation curves for moderate-contrast dark images generated for different values of μ and σ. Figure 2b shows the input dark image with a moderate contrast ($\mu = 0.20337$ and $\sigma = 0.18529$), the enhanced image using AGC algorithm ($\gamma = 1.3575$) and their respective histograms.

3 Proposed contrast enhancement method

SVD is considered to deal with an illumination problem and therefore to improve the contrast of dark images. SVD of
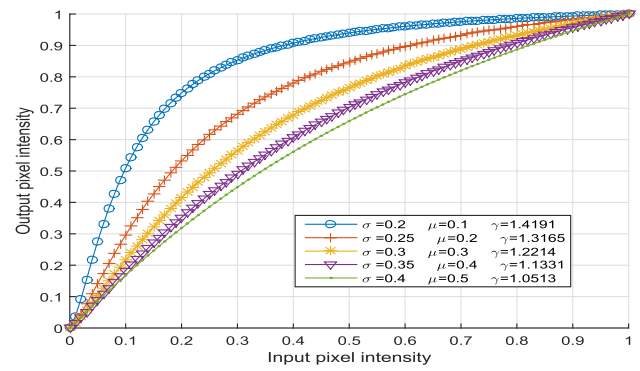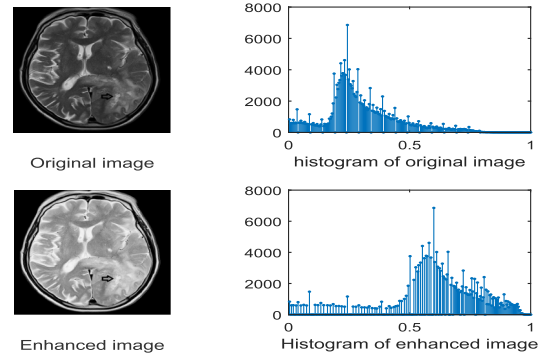
Fig. 2 Gamma correction for moderate contrast image: **a** Transformation curves for different values of μ and σ, **b** Original and enhanced images and their corresponding histograms

given input image I can be expressed as the product of three matrix [21].

$$I = U_I \sum_I V_I^T \tag{8}$$

where Σ_I is the singular value matrix which includes the sorted singular values on its main diagonal, U_I and V_I are two orthogonal square matrices labeled as hanger and aligner and T is transpose operator. The singular value matrix denotes the intensity information of the input image. Any modifications on the singular values will affect the intensity of the considered image; that is why SVD may be considered for image contrast enhancement. The enhancement process based on SVD utilizes a correction factor corresponding to the ratio of highest singular value of generated normalized matrix, with mean zero and variance of one, over a normalized image as given by Eq. (9).

$$\xi = \frac{\max \sum_{N(\mu=0,\sigma=1)}}{\max\left(\sum_I\right)} \tag{9}$$

where $\Sigma_{N(\mu=0,\sigma=1)}$ is the singular value matrix of the synthetic intensity matrix. The equalized image $I_{equalized}$ is hence calculated using Eq. (10).
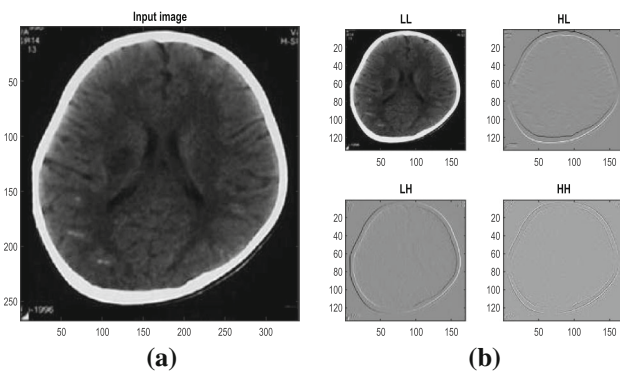
Fig. 3 **a** Original image, **b** Corresponding LL, LH, HL and HH subband images

$$I_{\text{equalized}} = U_I \left(\xi \sum{}_I \right) V_I^T \tag{10}$$

In the DWT–SVD technique, SVD is applied only on the low-frequency sub-bands witch are calculated using DWT [3]. Indeed, as shown in Fig. 3, enlightenment information is surrounded in LL sub-band but the edges are concerted in other sub-bands (i.e., LH, HL, and HH). Therefore, separating the high-frequency sub-bands and applying a contrast enhancement on only LL sub-band will protect the edge information from possible degradation. In this case, the input dark image I is processed using GHE algorithm in order to compute '$\hat{I}$.' Both images are decomposed into LL, LH, HL, and HH for 'I', and $\widehat{LL}$, $\widehat{LH}$, $\widehat{HL}$, and $\widehat{HH}$ for '$\hat{I}$' using DWT. In order to calculate the correction factor ξ, we considered the maximum element in U_{LL} and V_{LL}, from LL and the maximum element in $\hat{U}_{\text{LL}}$ and $\hat{V}_{\text{LL}}$ from $\widehat{LL}$ as given by Eq. (11) [26].

$$\xi = \frac{\max\left(\hat{U}_{\text{LL}}\right) + \max\left(\hat{V}_{\text{LL}}\right)}{\max\left(U_{\text{LL}}\right) + \max\left(V_{\text{LL}}\right)} \tag{11}$$

The enhanced singular value matrix $\bar{\Sigma}_{\text{LL}}$ and the enhanced LL sub-band image using SVD algorithm $\overline{\text{LL}}_{\text{SVD}}$ are, respectively, determined using Eqs. (12) and (13) [26].

$$\overline{\sum}{}_{\text{LL}} = \xi \ x \ \hat{\Sigma}_{\text{LL}} \tag{12}$$
$$\overline{\text{LL}}_{\text{SVD}} = \hat{U}_{\text{LL}} \ \bar{\sum}{}_{\text{LL}} \ \hat{V}_{\text{LL}}^T \tag{13}$$

After that, the enhanced LL sub-band using SVD approach, $\overline{\text{LL}}_{\text{SVD}}$, is classified according to Eq. (2) into either low-contrast class (C_1) or moderate-contrast class (C_2) depending on its statistical mean and standard deviation. The gamma correction factor for LL sub-band images from class C_1 and class C_2 is, respectively, computed using Eqs. (3) and (7). Adaptive gamma correction is applied on $\overline{\text{LL}}_{\text{SVD}}$ sub-band according to Eq. (14) to produce the final enhanced $\overline{\text{LL}}_\gamma$ sub-band image.

$$\overline{\text{LL}}_\gamma = c \cdot \left(\overline{\text{LL}}_{\text{SVD}}\right)^\gamma \tag{14}$$

where c is computed using Eqs. (4) and (15).

$$k = \left(\overline{\text{LL}}_{\text{SVD}}\right)^\gamma + \left(1 - \left(\overline{\text{LL}}_{\text{SVD}}\right)^\gamma\right) \cdot \mu^\gamma \tag{15}$$

The generated enhanced LL sub-band using gamma correction, $\overline{\text{LL}}_\gamma$, is recombined with others sub-band images of the original image (LH, HL and HH) using IDWT to generate the resultant equalized medical image '$\bar{I}$'.

$$\bar{I} = \text{IDWT}\left(\overline{\text{LL}}_\gamma, \text{LH}, \text{HL}, \text{HH}\right) \tag{16}$$

4 Experimental results

Miscellaneous experiments were conducted to assess and compare the performance of the proposed method with those of DWT–SVD technique [3], AGC [30] and knee and gamma correction using DWT–SVD technique (DWT–SVD–KGC) [26]. We considered the Meyer (dmey) wavelet as a mother wavelet with one level for images decomposition using DWT. The comparison is performed using both subjective and objective assessments.

4.1 Material

For objective evaluation, we considered a dataset including 300 high-resolution dark CT images of different sites of the body (the lungs, the brain, the liver, the pancreas and the kidneys). The dark CT images are selected from different medical databases like ctisus.com (http://www.ctisus.com) and radpod.org (http://www.radpod.org).

4.2 Subjective evaluation

Four dark CT images are chosen from the considered dataset for subjective evaluation. The original dark CT images and their corresponding histograms are, respectively, illustrated in Fig. 4(a$_1$–a$_4$) and (f$_1$–f$_4$). We note that the histogram of each original dark CT scan has a limited dynamic range and is not uniform.

Figure 4(b$_1$–b$_4$) and (g$_1$–g$_4$) shows the enhanced images using AGC algorithm and their corresponding histograms, respectively. The AGC algorithm enhances the contrast of considered dark CT images. It extends also their dynamic range and improves the uniformity of histograms. However, this enhancement algorithm adds some artefacts to the output images. In effect, an over-contrast enhancement is observed for some parts of the enhanced image, indicated by some peaks at the end of the grayscale range of the histogram. Moreover, a significant number of peaks remain at the begin-
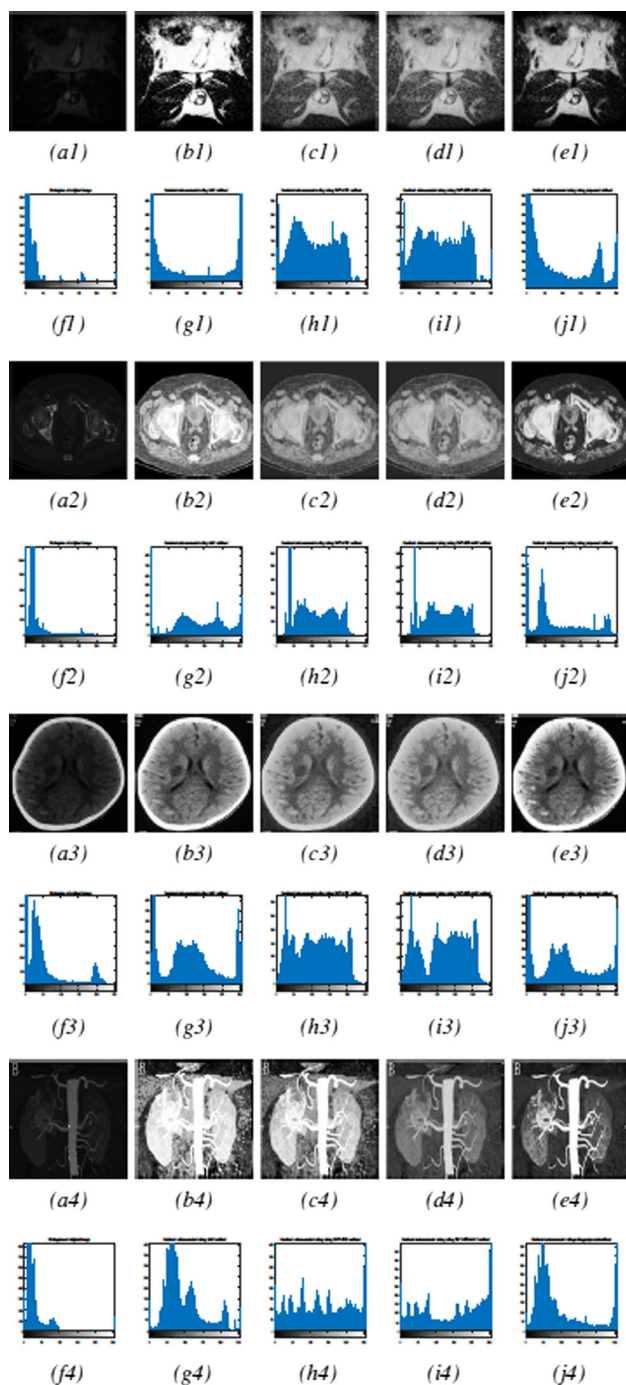
Fig. 4 Subjective evaluation of different contrast enhancement algorithms using dark CT images. $(a_1–a_4)$ and $(f_1–f_4)$: original dark CT images and their corresponding histograms, respectively, $(b_1–b_4)$ and $(g_1–g_4)$: enhanced CT images using AGC method and their corresponding histograms, respectively, $(c_1–c_4)$ and $(g_1–g_4)$ enhanced CT images using DWT–SVD method and their corresponding histograms, respectively, $(d_1–d_4)$ and $(h_1–h_4)$: enhanced CT images using DWT–SVD–KGC method and their corresponding histograms, respectively, $(e_1–e_4)$ and $(i_1–i_4)$: enhanced CT images using proposed algorithm and their corresponding histograms, respectively

ning and the end of the grayscale range, which leads to noise amplification.

Figure 4($c_1–c_4$) and ($h_1–h_4$) shows the enhanced images using DWT–SVD algorithm and their corresponding histograms, respectively. Figure 4($d_1–d_4$) and ($i_1–i_4$) illustrates the enhanced images using DWT–SVD–KGC and their corresponding histograms, respectively. DWT–SVD and DWT–SVD–KGC contrast enhancement algorithms present similar performances. Gamma correction has not a significant effect on the enhancement process in this case. Enhanced dark CT scans using both algorithms preserve the average brightness level and better enhance with overall image quality, but some edge details are lost in low and high intensity ranges. However, the low intensity range was not sufficiently enhanced and this could be explained by singular value constraint of the considered image. Additionally, both of considered contrast enhancement algorithms extend the dynamic range of the histogram slightly. In addition, histogram is uniform with reduced peaks and without any gaps, but some grayscale range, especially at the end, still uncovered.

Finally, Fig. 4($e_1–e_4$) and ($j_1–j_4$) shows the enhanced images using our proposed algorithm and their corresponding histograms, respectively. In our proposed contrast enhancement algorithm, we considered a second processing step in addition to DWT–SVD technique, leading to an additional improvement in image quality. The proposed algorithm provides the best results since enhanced images are naturally looking with higher contrast and sharper edges. In fact, a higher overall contrast enhancement with lower degradation and better conservation of edge details is observed. Furthermore, our proposed contrast enhancement algorithm covers the entire dynamic range, makes the histogram uniform, reduces the peaks and retains the shape similar to the original image.

4.3 Objective evaluation

Objective performance measures are very important in order to compare different contrast enhancement techniques. The performance of our proposed contrast enhancement method is evaluated and compared with different others contrast enhancement algorithms using image quality measurement tools. In this paper, we considered the Absolute Mean Brightness Error (AMBE) metric to evaluate the degree of brightness preservation, and better performances correspond to the enhancement algorithm with the small value of AMBE [24]. We considered also the Measure of Enhancement by Entropy (EME) as a second evaluation metric and better performance corresponds to higher value of EME [32]. The discrete entropy (H) is also considered for objective evaluation. In fact, the entropy is a measure of richness of
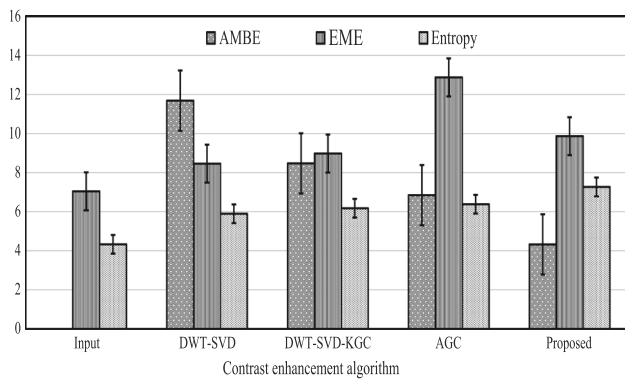
Fig. 5 Average values (±standard error) of AMBE, EME and H evaluation metrics

Fig. 6 Average value (± standard error) of QRCM evaluation metric

information in a given image after contrast enhancement and it is employed to assess the degree of contrast enhancement [24]. The Quality-Aware Relative Contrast Measure (QRCM) metric is also used for objective image quality assessment and better image quality is obtained with the QRCM value closest to unity [33]. Finally, we considered the Feature Similarity Index Measurement (FSIM) to compare the features of original and enhanced images [11]. FSIM∈ [-1,1], and better performances are obtained with higher FSIM values.

The totality of dark CT images included in considered database are processed using DWT–SVD, DWT–SVD–KGC, AGC and proposed contrast enhancement algorithms. Mean results for AMBE, EME and H evaluation metrics are summarized in Fig. 5.

The average AMBE values are, respectively, equal to 11.68, 8.47, 6.84 and 4.32 for DWT–SVD, DWT–SVD–KGC, AGC and proposed contrast enhancement algorithms. We note that AMBE value of our proposed algorithm is much lower than all other enhancement methods. Therefore, the proposed enhancement algorithm best conserves the image brightness.

The details of image are more visible when its overall contrast is increased, and this is indicated by higher EME values. Obtained average values of entropy are, respectively, equal to 7, 8.46, 7.97, 12.87 and 9.86 for input dark image and enhanced images using DWT–SVD, DWT–SVD–KGC, AGC and proposed contrast enhancement algorithms. In fact, simulation results showed that AGC enhancement algorithm gives much higher EME values than DWT–SVD, DWT–SVD–KGC, and proposed enhancement algorithms. However, due to severe augmentation in contrast, the enhanced images could present an unnatural look. Furthermore, the proposed algorithm gives improved EME value than DWT–SVD and DWT–SVD–KGC methods; but the change in EME is not as high as AGC method. Therefore, the images enhanced by the proposed algorithm are natural looking with better contrast and hence improved visibility of details.
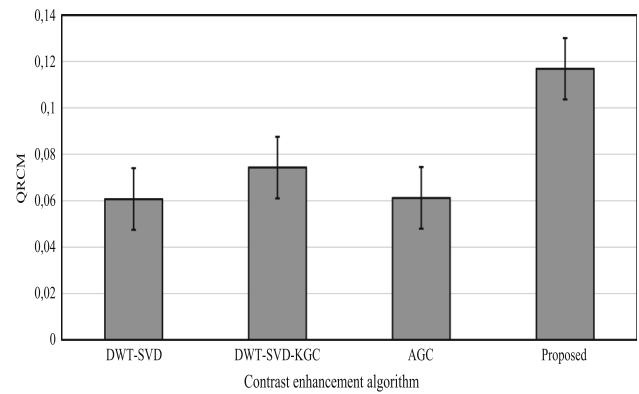
The average value of entropy of original dark images is equal to 4.33. Simulations results indicated that the proposed contrast enhancement algorithm preserves and improves the edges. This is confirmed by the most important average value of entropy ($H = 7.26$). The AGC contrast enhancement algorithm gives the second highest values of entropy ($H = 6.38$). Simulation results indicated also that average value of entropy for DWT–SVD contrast enhancement algorithm ($H = 5.89$) is slightly lower than DWT–SVD–KGC ($H = 6.17$).

We considered also the QRCM metric to assess and compare the performances of considered enhancement algorithms. Mean results are summarized in Fig. 6. We note that the proposed contrast enhancement algorithm offers the highest QRCM value (QRCM = 0.116) compared to others enhancement methods (average QRCM values are equal to 0.06, 0.0743 and 0.062 for DWT–SVD, DWT–SVD–KGC and AGC methods, respectively). Simulation results indicated also that both contrast enhancement algorithms developed by combining DWT–SVD with gamma transformation technique (DWT–SVD–KGC and proposed methods) performed better than DWT–SVD algorithm. This emphasizes that intensity transformation using gamma correction is a significant tool to improve the quality of enhanced image processed using only DWT–SVD method. Furthermore, computing adaptively and dynamically the gamma transformation parameters according to the statistical information of the image explains the higher performances of our proposed method compared to DWT–SVD–KGC where gamma transformation parameters are defined manually for each original image.

The average FSIM values are shown in Fig. 7. The proposed contrast enhancement algorithm presents the most important value of FSIM (FSIM = 0.948) signifying that the structure of original dark CT image is well conserved. The DWT–SVD–KGC contrast enhancement algorithm gives the second best value of FSIM (in this case, FSIM is equal to 0.86) and which is slightly higher than the FSIM value of
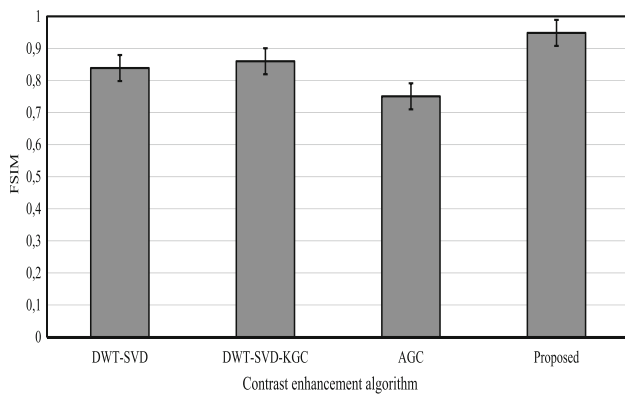
Fig. 7 Average value (± standard error) of FSIM evaluation metric

DWT–SVD method (where FSIM is equal to 0.838). However, AGC enhancement algorithm gives the lowest FSIM value (FSIM is equal to 0.75) indicating that some structures of original image are lost during the enhancement process. We can explain this ascertainment by the fact that when DWT–SVD-based methods are considered, only low frequency details of original dark CT image are processed (high-frequency image details are approximately not modified) which allow a preserving of the edge information of original image, contrary to AGC enhancement algorithm where the input image is processed in its totality.

Finally, we conclude that in addition to subjective evaluation, objective assessment approved that our proposed contrast enhancement algorithm consistently produces better results compared to other enhancement techniques.

5 Conclusion

In this paper, we proposed an adaptive gamma correction using DWT–SVD algorithm for dark CT image enhancement. The input image is processed using DWT–SVD method followed by gamma correction technique. Parameters of gamma transformation are adaptively computed according to the statistical information of the input image. Both subjective and objective experimental results showed higher performances for our proposed algorithm compared to others considered conventional enhancement methods. Furthermore, the proposed algorithm can enhance the contrast of dark input image with a higher preservation of brightness and with minimum loss of structural details and introduction of artifacts. This algorithm is well appropriated to improve the contrast of dark CT scan.

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