SOCIETY FOR SCIENCE AND EDUCATION
UNITED KINGDOM

JBEMi JOURNAL OF BIOMEDICAL ENGINEERING AND MEDICAL IMAGING

ISSN: 2055-1266
VOLUME 3 ISSUE 1

Enhancement of CT Images by Modified Object Based Contrast Stretching

Deepti Mittal, Kanika Sharma, Ritambhara Thakur, Abhay Krishan, Rishabh Singhal, and Anju Rani
Electrical and Instrumentation Engineering Department, Thapar University, Patiala (Punjab), India;
deepti.mittal@thapar.edu; kanika.3991@gmail.com; ritambhara3939@gmail.com;
abhaykrishan44@gmail.com; singhalrishabh21@gmail.com; anju.yaduvanshi@yahoo.com

ABSTRACT

The characteristic information of an organ lies in the texture of the image obtained by computed tomography imaging procedure. Therefore, enhancement of CT image aids a radiologist to better diagnose a disease which is a result of the enhanced/improved perceptibility and interpretability of the information present in the texture of the image. The present work proposes a method for texture enhancement of CT images by modifying Object-Based Multilevel Contrast Stretching method proposed by B. Xu et al. (IEEE Transaction on Consumer Electronics 3:1746-1754, 2010). In proposed method, a CT image is split into two images; (i) object approximation image and (ii) object error image. Object approximation image contains the overall structural information and object error image contains all the textural details of the CT image. The proposed method enhances the local contrast of object error image at an intra-object level, by greedy iterative stretch algorithm. Experimental results show that the proposed method enhances the textural details effectively, while maintaining the mean brightness of the image. Moreover, the quantitative results have verified that the proposed method outperforms the other methods.

Keywords: Intra-object;Texture, CT images; Enhancement; MOBCS.

1 Introduction

The computed tomography (CT) scan is one of the most common and important medical imaging modality. It is used, mostly, to evaluate the presence, size and location of the tumors present in a specific organ of the body. This evaluation is helpful in further diagnosis and confirmation of the disease. When a medical practitioner is involved in the diagnosis of a complicated case, such as detection and identification of liver cancer, texture contrast of a CT image plays an important role. Computed tomography images have good global contrast which can be further enhanced by adjusting window settings. Still, there is a limitation in the visualization of textural details in CT images. Improved visualization of texture may help to doctor in easy differentiation between various tumors, for example differentiation between liver cancer like Hepatocellular Carcinoma (HCC) and Metastasis [1-3]. This improvement in localized contrast of an image can make even small tumors or infections perceptible. A tumor is an abnormal growth of tissues, and there is a difference in the characteristic information of

DOI: 10.14738/jbemi.31.1828
Publication Date: 29th February 2016
URL: http://dx.doi.org/10.14738/jbemi. 31.1828

normal tissues and abnormal tissues. This characteristic information regarding tissues exists in the texture of CT images. Therefore, there is a need for an enhancement method for better texture visualization. This improvement in texture visualization will aid the doctor with improved perceptibility and interpretability of information enclosed by the image. Further, the enhancement of texture helps to doctor, in easy confirmation and better diagnosis of disease. Overall, the quality of CT images is of high significance to the doctor for better diagnosis with less fatigue. Further, the image quality depends on various parameters such as noise, spatial resolution, artifacts, contrast etc. In the present work, the quality of CT images is improved by enhancing contrast of the texture.

Among the various enhancement methods in literature on medical and non-medical images, global histogram equalization (GHE) is the most commonly used method for contrast enhancement [4]. The method enhances the contrast and dynamic range of an image by (i) stretching the grey levels of an image histogram over full intensity range and (ii) creating a uniform distribution of intensity levels. The limitation of GHE is that it occasionally introduces over enhancement and saturation artifacts. Local histogram equalization (LHE) is an extension of GHE, which helps in enhancement of the local details of an image [4, 5]. LHE method is implemented by moving a window of suitable size on the image and then transformation function of GHE is applied only to the part of image which is covered by the window. However LHE also enhances the noise alongwith details of the image. Zhu *et. al.* proposed a constrained local histogram equalization method to remove the drawback of LHE and preserve the overall appearance of the image [5]. In this method variational formulation of histogram equalization (HE) is extended directly to LHE and a constraint is added to preserve the original appearance of the image. Another approach for enhancement based on Histogram is Multi-peak generalized histogram equalization method [6]. The method enhances the texture alongwith the contrast of images. The enhancement is performed by piecewise partitioning and equalizing the image histogram according to the proposed generalized transformation function of histogram equalization. Constrained local histogram equalization and MPGHE methods have not been applied to medical images. Tsai *et. al.* proposed an adaptive enhancement algorithm which enhances the CT medical images by removing noise without considerably blurring the structures in the image [7]. Noise is removed by adaptive smoothing filter. The drawback of this method is that it loses the local textural details of the image due to the effect of smoothing filter. Jafar and Ying proposed a method based on the extension of GHE i.e., Constrained variational histogram equalization [8]. The method overcomes the shortcoming of GHE by preserving the mean brightness of the image while enhancing the contrast of the image. It is based on the variational approach of HE and a constraint added to transformation function of variational GHE preserves the mean brightness of the image. This method improves the drawback of GHE but it does not enhance the local details of the image. Another approach for contrast enhancement simultaneously preserving the overall appearance of the image is histogram modified local contrast enhancement [9]. This method involves the modification of histogram to control the enhancement levels and local contrast enhancement technique for local details enhancement of the image. This method has been tested on mammogram images and delivered effective results. Tan *et. al.* proposed extreme level eliminating adaptive histogram equalization method [10]. The method is used to enhance CT images of the brain for ischemic stroke detection. In this method, the image is first split into non overlapped sub-blocks, and then each sub block is equalized by extreme level eliminating equalization transformation function. This is an efficient method but it focuses mainly on enhancing the hypo-dense area in CT images. An intensity adaptive nonlinear multi-scale contrast enhancement method is proposed to enhance the contrast and details of digital radiography [11]. This method has steps of enhancement including noise reduction, range compression, detail enhancement, contrast enhancement, tone scale-up manipulation. Another method, based on histogram manipulation, is proposed by Sharma and Mittal i.e., histogram equalization with constrained variational offset (HECVO) [12]. This method enhances the texture of the CT images and is based on the modification of histogram equalization. The modification is done by adding a constrained variational offset to the transformation function of HE, this offset helps in preserving the mean brightness and global appearance of the image. This method enhances the contrast of CT image effectively but is limited to global enhancement. Wang *et. al.* proposed a medical image enhancement method based on non sub-sampled contourlet transform and improved fuzzy contrast [13]. In this method, linear enhancement method is used to deal with low frequency coefficients and threshold function is used to handle the high frequency coefficients. Finally, improved fuzzy contrast is used for global enhancement and Laplace operator is used for local or detail enhancement. This method is suitable for detail enhancement of medical images but the enhanced results specifically for CT images shows some distortion from the original image. Another approach for contrast enhancement of CT images is tuned brightness controlled single-scale retinex proposed by Al-Ameen and Sulong [14]. This method is extension of the single-scale retinex (SSR), which includes tuning of SSR and inserting a normalized-ameliorated sigmoid function. This method enhances the contrast but it does not emphasize on the improvement of the textural detail. Object based multilevel contrast stretching (OBMCS) method is another approach for contrast enhancement [15]. It enhances the contrast of the image at two levels: inter-object and intra-object with different enhancement algorithms. Inter-object level enhances the structures of the image by greedy iterative stretch algorithm and intra-object level enhances the textural details of the image by linear contrast stretching. OBMCS method has been tested on consumer electronics images but it has not been applied to the CT images.

In present work the modified object based contrast stretching (MOBCS) enhancement method is proposed and applied on CT images. CT images have good structural and global details. Further processing on CT image at inter-object level creates over enhancement and it may lead to false interruption of structural details. Therefore, MOBCS is designed with intra-object enhancement principally to improve the visibility of textural details in CT images. Therefore, the method is implemented by (i) modification in OBMCS method with single level enhancement only at object error image for texture contrast enhancement of CT images and (ii) addition of a parameter to preserve the mean brightness of original image. The proposed research work is organized as follows: section-II includes background of the method with some basic definitions and methods used in the proposed method, brief description of OBMCS method, proposed method and performance measures. Section-III includes results and discussion and section- IV describes the final conclusion of the paper.

2 Methods

2.1 Background

In this section, the basic methods used in formation of the proposed method i.e., segmentation method and contrast stretching method, are discussed. Morphological watershed segmentation method is used for segmentation of the image to obtain the objects with homogenous intensities [4, 16, 17]. According to the basic idea of watershed segmentation an image can be seen as a relief-map with intensity values denoting elevation of the map. Assume a hole is punched in the regional minimum and therefore relief-map is flooded with water from bottom of the catchment basin at uniform rate. When the two catchment basins are about to merge a short dam is constructed to prevent merging of water. These dams are interpreted as watershed lines and these lines are the desired segmentation result of the image. The watershed method is applied to the gradient image not on the original image directly.

Watershed segmentation method is very sensitive, even to small variation of intensities. Therefore, it sometimes generates over-segmentation. Over segmentation can be avoided by (i) pre-processing of the gradient image and (ii) and post-processing of the segmented image. The pre-processing is accomplished by gradient thresholding and the post-processing is implemented by region merging [4]. The implementation of gradient thresholding is shown in next sub-section. Region merging is applied to merge the segments created by watershed method and implemented by merging of the adjacent segments step by step with a merging criterion [16, 17]. In addition, the merging of adjacent segments can be arrested by adding a specific stopping condition. Further, the performance of the merging of segments is highly influenced by the merging criterion which is being used for region merging. In literature, a number of merging criteria have been proposed which are broadly dependent on (i) the features of segmented region and (ii) the dissimilarity function. Ward criterion, just noticeable difference criterion, mean criterion, ward-mean criterion, border criterion, linear luminance criterion etc are the examples of merging criteria based on the features of a segmented region [18]. Stopping condition δ_t for region merging can depend on the estimated standard deviation of noise σ of original image [19]. Finally, Region merging algorithm is implemented efficiently by region adjacency graph (RAG) [16].

Contrast stretching in the proposed method is done by greedy iterative stretching [20]. This method enhances the local contrast of the image. Here, the image is visualized as a grid of size M×N and intensity of the pixel as height of the grid. For each iteration a threshold plane is decided and non-zero connected components are calculated for the image grid pixels which are above the threshold plane. The set of connected components is known as hillock. All hillocks are scaled according to certain constraints. The threshold planes are swept iteratively between the lower and upper limits decided for image and accordingly hillocks are scaled. The image is inverted and the sweep and scaling process is applied to inverted image. The image is again inverted for getting the contrast enhanced image.

2.2 Object based multilevel contrast stretching method

Object based multi level contrast stretching method is proposed by Xu et al. The method first obtains the gradient magnitude image, $G(i,j)$ from the original image, $I(i,j)$ using sobel operator. The mathematical formula is as follows:

$$G(i,j) = \left|G_i(i,j)\right| + \left|G_j(i,j)\right| \tag{1}$$

where $G_i(i,j)$ and $G_j(i,j)$ are the gradient components in horizontal and vertical direction respectively.

On the acquired gradient magnitude image, the gradient threshold is applied to prevent over segmentation before watershed segmentation. Gradient thresholding is implemented as follows:

$$G_n(i, j) = \begin{cases} G_t & if\ G(i, j) < G_t \\ G(i, j) & otherwise \end{cases} \tag{2}$$

where G_n is new gradient image after thresholding, G_t is gradient threshold which helps in prevention of over segmentation. After thresholding, gradient magnitude image is served as an input to the watershed segmentation method. After applying watershed method, region merging is applied as post processing for prevention of over segmentation. Xu et al., applied mean criterion for region merging on segmented result obtained by watershed method. The dissimilarity function for mean criterion of region merging is:

$$\delta(S_i, S_j) = \left|\mu(S_i) - \mu(S_j)\right| \tag{3}$$

where $\mu(S)$ denotes the mean of the region S. The mean criterion merges pairs of adjacent region comprising value of dissimilarity function less than the assigned stopping condition δ_t. The image is further divided into two sub images, (i) object approximation image (OAI) and (ii) object error image (OEI). Object approximation image, denoted by $I_a(i, j)$ is obtained by replacing each pixel in the original image by mean intensity value of the corresponding region. Object error image, denoted by $I_e(i, j)$, is calculated by subtracting the OAI from original image. The mathematical representation of OAI and OEI is as follows:

$$I_a(i, j) = \mu(S_{(i,j)}) \tag{4}$$

$$I_e(i, j) = I(i, j) - I_a(i, j) \tag{5}$$

The original image $I(i, j)$ can be obviously obtained using eq. (4) and (5):

$$I(i, j) = I_a(i, j) + I_e(i, j) \tag{6}$$

In OBMCS method, the inter-object contrast enhancement of OAI is accomplished by greedy iterative stretching proposed by Majumder and Irani (2007) and intra-object contrast enhancement of OEI is done by linear contrast stretching. Finally, both enhanced images are combined to get the final enhanced result.

2.3 Proposed method

The proposed method comprises of single level of contrast stretching i.e. intra-object contrast enhancement because it leads to textural features enhancement, which is required for CT images. Since, CT images have good structural and global details; the inter-object contrast stretching is not performed for CT images as it may lead to false interpretation of structural detail. Flow chart of proposed method is shown in Figure 1 and the steps involved are explained in detail as follows:

STEP 1: Segmentation using watershed method

Watershed method produces stable close object contours in segmentation results. To avoid over segmentation produced by watershed pre and post processing is applied on the image. The pre-processing applied is gradient thresholding represented by eq. (1) and (2). The post- processing is similar to that of OBMCS method i.e., region merging, but there is a change in merging criterion used for region merging. Ward criterion is used in the proposed method because it is superior from mean criterion as it tends to minimize the total square error introduced by merging of two adjacent regions and it merges small regions not large ones. Ward criterion also eliminates noise and double edges [16, 21]. The dissimilarity function for ward criterion of region merging is:

$$\delta(S_i, S_j) = \frac{\|S_i\| \cdot \|S_j\|}{\|S_i\| + \|S_j\|}\left[\mu(S_i) - \mu(S_j)\right]^2 \tag{7}$$

where $\|S\|$ is the number of pixels in region S .

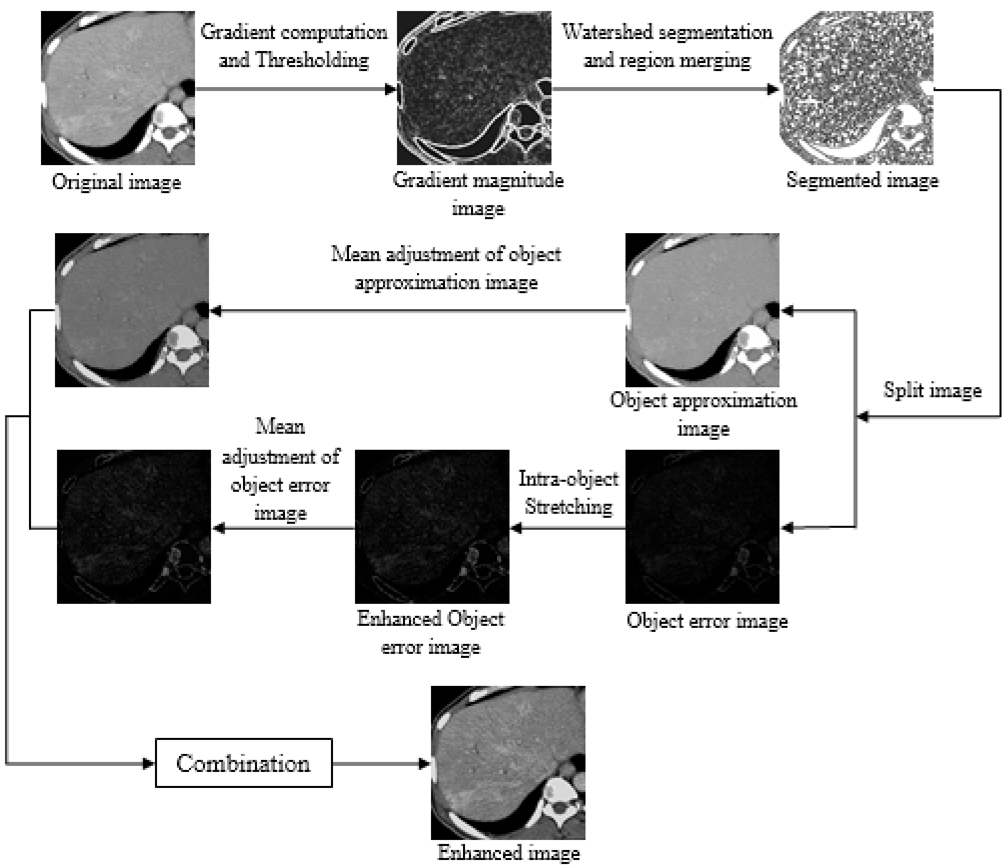

Figure 1. Flow chart of proposed method.

STEP 2: Intra-object contrast stretching

The object approximation image and object error image is constructed as shown in eq. (4) and (5). Intra-object contrast stretching is obtained by enhancing the contrast of the OEI. Object error image contains the textural details and by enhancing it, textural details of CT images get enhanced. The OEI is enhanced using greedy iterative stretching unlike OBMCS where it is linearly stretched. The proposed method enhances the local contrast of texture part, so it uses greedy iterative stretching method for intra-object enhancement. The intra-object contrast stretching is carried out with the following constraints:

$$1 \le \frac{I'(i,j) - \mu'(S_{(i,j)})}{I(i,j) - \mu(S_{(i,j)})} \le (1+\lambda) \tag{8}$$

$$L \le I'(i,j) \le U \tag{9}$$

where $I(i,j)$ is original image, $I'(i,j)$ is enhanced image, $\mu(S_{(i,j)})$ is mean of region S of original image, $\mu'(S_{(i,j)})$ is mean of region S of enhanced image, λ is a parameter that controls the amount of enhancement, L and U are the lower (0) and upper (255) limit of gray scale intensity range, respectively. Constraints in eq. (8) and (9) are added to control the amount of contrast stretching and to eliminate the saturation effects in enhanced image. The greedy iterative stretching involves sweeping of threshold plane from L to U iteratively and stretching the hillocks (set of connected components in image matrix containing pixel values above threshold plane) greedily while taking the mentioned constraints into account. To further enhance the image, image is inverted and the same procedure of sweeping threshold plane is applied. After stretching the image is again inverted to obtain final enhanced OEI, $I'_e(i,j)$. Enhancement of OAI is not required in case of CT images.

STEP 3: Mean adjustment in OAI and OEI

The enhanced image obtained after combining the enhanced OEI with original OAI results in overall increment in brightness. To preserve the brightness of the image with enhanced textural details some mean adjustments are made. Before combining the two images, some percentage of mean of OAI is subtracted from the original OAI and similarly some percentage of mean of enhanced OEI is added to the enhanced OEI. This is implemented as follows:

$$newI'_e(i,j) = I'_e(i,j) + \alpha\% \; of \;\; \mu(I'_e(i,j)) \tag{10}$$

$$newI_a(i,j) = I_a(i,j) - \alpha\% \; of \;\; \mu(I_a(i,j)) \tag{11}$$

The value of α will decide the amount of global brightness of the image. Final enhanced image is obtained by combining the images calculated in eq. (10) and (11):

$$F(i,j) = newI'_e(i,j) + newI_a(i,j) \tag{12}$$

where $F(i,j)$ is final enhanced image.

2.4 Performance evaluation

The performance of enhanced CT images is evaluated by five performance parameters. The parameters are as follows:

2.4.1 Correlation Coefficient (ρ)

The correlation coefficient (ρ) measures the degree of linear correlation between the original and processed images [22]. ρ between original image $I(i, j)$ and enhanced image $F(i, j)$ of size $M \times N$ is expressed as given below:

$$\rho = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} F(i,j)I(i,j)}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j))^2}\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(F(i,j))^2}} \tag{13}$$

2.4.2 Universal Image Quality Index (Q)

The universal image quality index measures the distortion between original and processed image [22, 23]. Mathematical representation is as follows:

$$Q = \frac{\sigma_{IF}}{\sigma_I \sigma_F} \cdot \frac{2\bar{F}\bar{I}}{(\bar{F})^2 + (\bar{I})^2} \cdot \frac{2\sigma_I \sigma_F}{\sigma^2{}_I + \sigma^2{}_F}, \quad -1 < Q < 1 \tag{14}$$

where $\bar{I}$ and $\bar{F}$ represent the mean of the original and processed images respectively. First component in the mathematical formula represents the linear correlation between the original and processed image, second component represent the local luminance and last component represents similarity of contrast between the two images. The higher values of Q show less distortion in the processed image.

2.4.3 Pratts's Figure of Merit (FOM)

The mathematical representation of FOM is as follows:

$$FOM = \frac{1}{\max(E, E_{ideal})} \sum_{i=1}^{E} \frac{1}{1 + d_i{}^2 \tau} \tag{15}$$

where E, E_{ideal}, d_i are the detected edges, ideal edges, Euclidean distance between i[th] detected pixel and its neighboring pixel respectively. τ is a constant mostly set to 1/9 [22, 24].

2.4.4 Feature Similarity Index ($FSIM$)

Feature similarity index measures the image local quality based on the low-level features of two images such as phase congruency and gradient magnitude [15]. Mathematical representation of $FSIM$ calculated between the original image $I(i, j)$ and enhanced image $F(i, j)$ is as follows:

$$FSIM = \frac{\sum_{i,j \in \Omega} Z_L(i,j) \cdot P_m(i,j)}{\sum_{i,j \in \Omega} P_m(i,j)} \tag{16}$$

where Ω is spatial domain image, $P_m(i, j)$ is maximum of phase congruency map of original and enhanced images and $Z_L(i, j)$ is given as:

$$Z_L(i,j) = \left[Z_P(i,j)\right]^x \cdot \left[Z_G(i,j)\right]^y \quad (17)$$

where Z_p is similarity measure for phase congruency of original and enhanced images, and Z_G is similarity measure for gradient magnitude of original and enhanced images. The higher values of FSIM show the better image quality.

2.4.5 Mean Structural Similarity Index ($MSSIM$)

Mean structural similarity index measures the similarity between structural information of original image and enhanced image [26]. The mathematical representation of $MSSIM$ is as follows:

$$MSSIM(I,F) = \frac{1}{R}\sum_{k=1}^{R} SSIM(I_k, F_k) \quad (18)$$

where I and F are original and enhanced images respectively, $SSIM(I_k, F_k)$ is structural similarity measure of original image and enhanced image at k^{th} local window and R is the number of total local window.

3 Experimental Results and Discussion

The proposed MOBCS method is implemented in MATLAB version 7.10 on a PC with Intel core i5 (2.5 GHz) processor. In this research, 197 liver CT images, 20 out of which are images with HCC lesion, 82 with metastasis and 95 images of a normal liver were collected from Max Saket Hospital, New Delhi. These liver CT images were acquired from 4 different patients (male). The liver CT images were collected from the hospital in the form of DICOM format images and converted to portable network graphics (png) format and all images have their own clinical settings such as window width, window level, slice thickness etc. The proposed method is applied and tested on a data set of these liver CT images of size 514×514.

Subjective evaluation of performance of the method is examined by three different radiologists; one is an intern radiologist, a radiologist with the experience of less than five years and other with experience of more than 10 years. According to visual inspection of three radiologists, the proposed method is appropriate for enhancement of the texture of CT images and they suggest verifying the results with various objective evaluation procedures to validate the effectiveness of the method in general.

Objective evaluation is performed by correlation coefficient, Pratt's figure of merit, universal image quality index, feature similarity index and mean structural similarity index. These quantitative measures are also calculated for Contrast limited adaptive histogram equalization (CLAHE) and HEVCO method for comparison with proposed MOBCS method.

Table 1. Comparison of performance measures for enhancement methods.

Performance measures	CLAHE	HEVCO	MOBCS
ρ	$0.9871 \pm 6.5973\times10^{-06}$	$0.9872 \pm 3.1298\times10^{-05}$	$0.9929 \pm 5.5659\times10^{-06}$
Q	$0.9167 \pm 5.4600\times10^{-04}$	$0.9144 \pm 1.4550\times10^{-03}$	$0.9421 \pm 3.8845\times10^{-05}$
FOM	$0.5678 \pm 1.8169\times10^{-02}$	$0.5798 \pm 1.7507\times10^{-02}$	$0.6601 \pm 1.2709\times10^{-02}$
FSIM	$0.8467 \pm 2.6500\times10^{-04}$	$0.7942 \pm 2.1070\times10^{-03}$	$0.9378 \pm 2.9496\times10^{-05}$
MSSIM	$0.6989 \pm 6.7800\times10^{-04}$	$0.5091 \pm 2.1730\times10^{-02}$	$0.8378 \pm 9.0932\times10^{-04}$

Table-1 summarizes the results of these quantitative measures in the form of mean and variance to reduce sample bias. The first performance measure is correlation coefficient (ρ) that is used to find out the similarity between original and processed image. The dynamic range of correlation coefficient is [-1, +1], where +1 represents the images are positively correlated and -1 represents images are negatively correlated. The value of correlation coefficient for CLAHE method varies from 0.9815 to 0.9912 for data set of CT images and represented as the mean value i.e., 0.9871 in table 1. The value of ρ for HECVO method varies from 0.9702 to 0.9927 and the mean value is 0.9872, which is almost equal to that of CLAHE method. The value of ρ for proposed method varies from 0.9871 to 0.9951 and the mean value is 0.9929, which is highest among all of the three methods. This shows that MOBCS processed images comprise highest correlation with their corresponding original images. The second performance measures is universal image quality index (Q) and the range of Q is also [-1, +1], where value 1 shows that processed image is not at all distorted i.e., processed image is similar to the original image. Higher values of Q represent less distortion. Enhancement is an image processing strategy which sets changes in the intensity of the image, so that the processing that enhances the image may distort the information of the original image, but the changes occuring due to enhancement must not be so high that the processed image loses its original details. The minimum and maximum value of Q obtained by applying CLAHE method is 0.8854 and 0.9656 respectively also the mean value of Q is 0.9167. The value of Q for HECVO method varies from 0.8130 to 0.9692 and the mean value is 0.9144. The value of Q for proposed method varies from 0.9330 to 0.9575 and the mean value is 0.9421. The proposed method posses highest value of Q among all the three methods, which shows that Q is also improved for MOBCS method and there is less misrepresentation in enhanced images by proposed method than CLAHE and HEVCO method. The third performance measure is Pratt's figure of merit (FOM) which represents the edge preservation of the processed images. Its value lies in between 0 and 1, where 1 shows highest preservation of edges. The value of FOM for CLAHE method varies from minimum value 0.3883 to maximum value 0.8207 and the mean value of FOM is 0.5678. The value of FOM for HECVO method varies from minimum value 0.3627 to maximum value 0.8183 and the mean value is 0.5798. The value of FOM for proposed method varies from minimum value 0.4915 to maximum value 0.8672 and the mean value is 0.6601. The results confirm that the proposed method outperforms the other two methods. This shows that edge quality is also better for MOBCS method than other two methods. The fourth performance measure is feature similarity index (FSIM) and it is used to calculate the similarity of local level features and local quality between original image and processed image and its value ranges between 0 and 1, value 1 shows the highest feature similarity between original and processed image. The value of FSIM for CLAHE method varies from 0.8258 to 0.8796 and the mean value is 0.8467. The value of FSIM for HECVO method varies from 0.6775 to 0.8520 and the mean value is 0.7942. The value of FSIM for MOBCS method varies from 0.9196 to 0.9452 and the mean value is 0.9378. The value of FSIM is highest for the proposed method, this shows that proposed method gives highest similarity between original and processed image. The last performance measure is mean structural similarity index (MSSIM) and its high values represent more structural similarity between original and processed image. The minimum value of MSSIM calculated for CLAHE method is 0.6722, the maximum value is 0.7635 and the mean value is 0.6989. The value of MSSIM calculated for HECVO method varies from minimum value 0.1189 to maximum value 0.6844 and the mean value is 0.5091. The value of MSSIM for proposed method varies from 0.7648 to 0.8759 and the mean value is 0.8378, which is highest among the compared methods. This shows that image enhanced by proposed method has better structural similarity with original image. The proposed method outperforms the other two methods for all the five performance measures. The box and whisker plot of five performance measures for the proposed method, CLAHE method and HECVO method are shown in Figure 2. The variability and distribution of performance measures calculated for CT image data set of proposed method are compared with other methods. From figure 2, it is clear that the ranges of all the performance measures for proposed method are narrow and variability from minimum to maximum value is quite less for the proposed method in comparison to other methods. This shows that the proposed method produces enhancement results that are stable for all CT images.

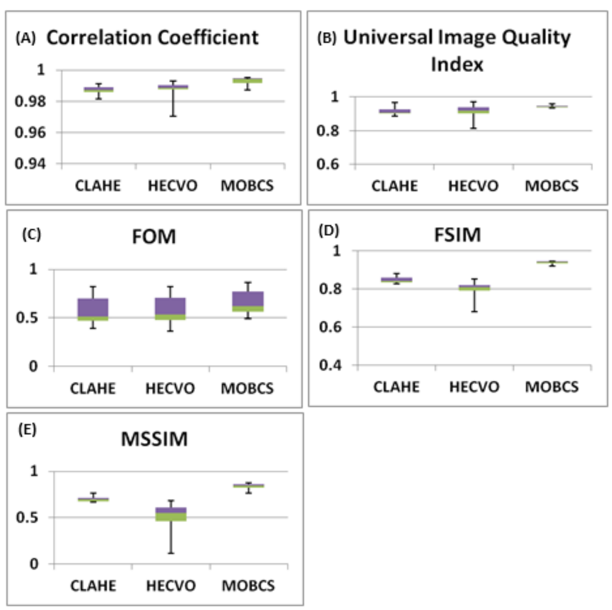

Figure 2. Box plot for comparison of performance measures results of proposed method with CLAHE and HECVO method. Plots (A), (B), (C), (D) and (E) show comparison of correlation coefficient, universal image quality index, figure of merit, feature similarity index and mean structural similarity index respectively

In figure 2, plots (A), (B), (C), (D) and (E) show the comparison of correlation coefficients, universal image quality index, figure of merit, feature similarity index and mean structural similarity index respectively for the three methods. Figure 3 shows the original images with their corresponding enhanced image results obtained by the proposed method.

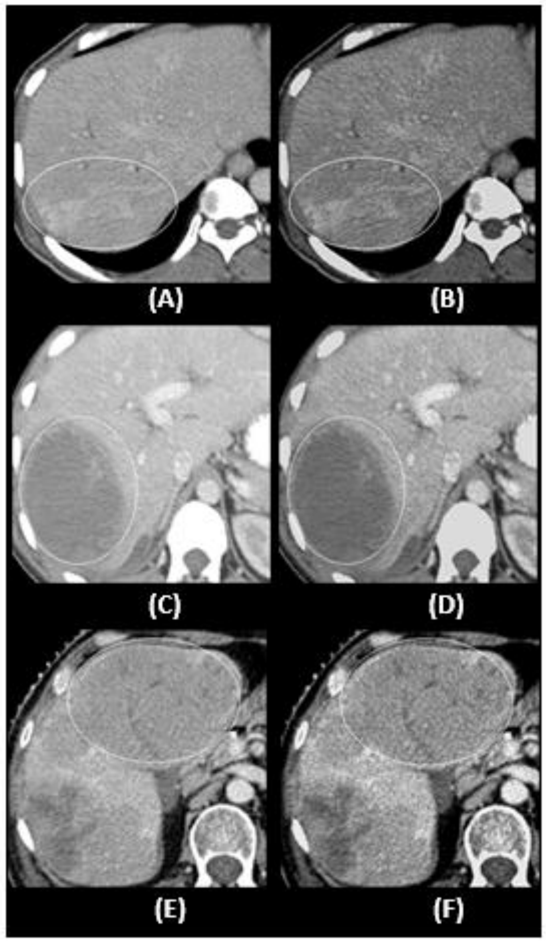

Figure 3. Image enhancement results by proposed method. Images (A), (C) and (E) are the original images with tumor and images (B), (D) and (F), are the corresponding enhanced images.

In Figure 3, images (A), (C), (E), are the original CT images of a patient suffering from liver cancer and the cancerous part is marked by white circular marker and images (B), (D), (F), are the corresponding enhanced images. Images (A) and (B), in Figure 3 contain HCC lesion and images (C), (D), (E) and (F) contain metastasis. The tumor part is clearly visible in the enhanced images and it is easier to differentiate between normal texture and tumor part in the enhanced images. The liver texture part of original image and enhanced image is shown in figure 4, where images (A) and (C) are the original images and images (B) and (D) are the corresponding enhanced images. From figure 4, texture enhancement is clearly visible.

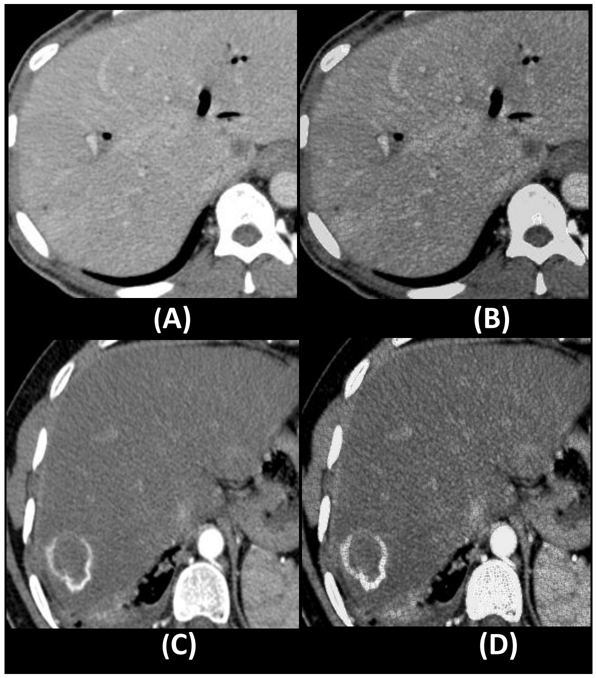

Figure 4. Comparison of texture of enhanced images with original images. Images (A) and (C) are original image and, images (B) and (D) are enhanced images.

The enhanced results obtained by varying the parameters i.e., gradient threshold G_t, stopping condition for region merging δ_t, threshold for contrast stretching λ, mean percentage α. Many experiments have been conducted to obtain the ideal values of parameters that can serve as the desired enhancement of texture of CT images. To accomplish this, first experiment is carried out by varying the gradient threshold G_t and it is tuned to 0.015 times of the estimated standard deviation of noise σ_e. The second experiment is conducted to obtain stopping condition δ_t for region merging. δ_t is varied to suppress the over enhancement and tuned to 5 times of σ_e for best enhanced results. Third experiment is done for λ, it is varied to obtain the required contrast enhancement of texture part. λ equal to 0.8 is the optimal observed value for enhancement. The values less than 0.8 give less contrast enhancement and values higher than 0.8 result in over enhancement. Final experiment is conducted to find the optimal value for mean percentage α. The mean percentage constant α is varied between 10% to 50% and tuned to 30% to preserve global look and textural details of the enhanced image.

4 Conclusion

Objective of this paper is to develop an enhancement method that aids in the enhancement of textural details of CT images. Enhancement of CT images is required to easily diagnose the infection, lesion or tumor. The proposed MOBCS method enhances the textural features and details of CT images effectively with preservation of the global outlook of the image. Performance of the proposed method is evaluated by various quantitative measures. The quantitative performance measures are compared with CLAHE and HECVO method and according to the results, it is observed that MOBCS outperforms other methods in terms of (i) edges preservation, (ii) distortion produced due enhancement and (iii) preservation of structural similarity of enhanced image with original image. Therefore, it can be concluded that the textural detail enhancement by MOBCS method is quite efficient for better disease diagnosis.

ACKNOWLEDGMENT

The authors thank to Max Saket Hospital, New Delhi for supporting the research.

REFERENCES

[1] D. Mittal, V. Kumar, S. C. Saxena, N. Khandelwal and N. Kalra. Neural network based focal liver lesion diagnosis using ultrasound images. Computerized Medical Imaging and Graphics 2011; 35:315–323.

[2] A. Krishan and D. Mittal, 2015. Detection and Classification of Liver Cancer using CT Images. International Journal on Recent Technologies in Mechanical and Electrical Engineering 2, 93-98.

[3] Ritambhara and D. Mittal, 2015. Segmentation of Liver from Abdomen CT images and 3D Visualization. Journal of Biomedical Engineering and Medical Imaging 2, 46-55.

[4] R.C. Gonzalez, R.E. Woods. Digital Image Processing, 3rd edition. Prentice Hall, 2002.

[5] H. Zhu, F.H.Y. Chan, F.K. Lam. Image contrast enhancement by constrained local histogram equalization. Computer vision and image understanding 1999; 73:281-290.

[6] H.D. Chang and X.J. Shi. A simple and effective histogram equalization approach to image enhancement. Digital signal processing 2004; 14:158-170.

[7] D.Y. Tsai, N. Takahashi, and Y. Lee. An Adaptive Enhancement Algorithm for CT Brain Images. IEEE proceedings, Engineering in Medicine and Biology 27th Annual Conference 2005.

[8] I. Jafar and H. Ying. Image contrast enhancement by constrained variable histogram equalization. IEEE IET proceedings 2007; 120-125.

[9] M. Sundaram, K.Ramar, N. Arumugam and G. Prabin. Histogram modified local contrast enhancement for mammogram images. Applied soft computing 2011; 11:5809-5816.

[10] T. L. Tan, K. S Sim, C. P. Tso and A. K. Chong. Contrast Enhancement of Computed Tomography Images by Adaptive Histogram Equalization-Application for Improved Ischemic Stroke Detection. International Journal of Imaging System Technology 2012; 22:153–160.

[11] Ostojic, D. Starcevic and V. Petrovic. Artifact reduction in multi-scale contrast enhancement for digital radiography. 22nd Telecommunications forum TELFOR 2014; 513:516.

[12] K. Sharma and D. Mittal. Contrast enhancement technique for CT images. Journal of biomedical engineering and medical imaging 2015; 2:44-50.

[13] J. J. Wang, Z. H. Jia, X. Z. Qin, J. Yang and N. Kasabov. Medical Image Enhancement Algorithm Based on NSCT and the Improved Fuzzy Contrast. International Journal of Imaging Systems and Technology 2015; 25:7-14.

[14] Z. Al-Ameen and G. Sulong. A New Algorithm for Improving the Low Contrast of Computed Tomography Images Using Tuned Brightness Controlled Single-Scale Retinex. Scanning 2015; 37:116-125.

[15] B. Xu, Y. Zhuang, H. Tang, and L. Zhang. Object based multilevel contrast stretching for image enhancement. IEEE transactions on consumer electronics 2010; 56:1746-1754.

[16] K. Haris, S.N. Efstratiadis, N. Maglaveras and A.K. Katsaggelos. Hybrid image segmentation using watersheds and fast region merging. IEEE Transactions on image processing 1998; 7:1684-1699.

[17] X. C. He, R. H. Y Chung and N. H. C. Yung. Watershed segmentation with boundary curvature ratio based merging criterion. Proceedings of IASTED International Conference on Signal and Image Processing 2007; 7-12.

[18] T. Brox, D. Farin, P. H. N. de With. Multi-stage region merging for image segmentation. Symposium on Information and Communication Theory in the Benelux 2001; 189-196.

[19] S. Olsen. Estimation of noise in images: An evaluation. CVGIP: Graph. Models Image Process 1993; 55:319–323.

[20] Majumder and S. Irani. Perception Based Contrast Enhancement of Images. ACM Transactions on Applied Perception 2007; 4:1-22.

[21] J. H. Ward. Hierarchical grouping to optimize an objective function. Journal of American Statistical Association 1963; 58:236–245.

[22] D. Mittal, V. Kumar, S. C. Saxena, N. Khandelwal and N. Kalra. Enhancement of ultrasound images by modified anisotropic diffusion method. Medical and Biological Engineering and Computing 2010; 48:1281–1291.

[23] Z. Wang and A. C. Bovik. A universal image quality index. IEEE signal processing letters 2002; 9:81-84.

[24] E. Abdou and W. K. Pratt. Quantitative design and evaluation of enhancement/ thresholding edge detectors. Proceedings of the IEEE 1979; 67:753-763.

[25] L. Zhanga, Lei Zhang, X. Mou and D. Zhang. FSIM: A Feature Similarity Index for Image Quality Assessment. IEEE transactions on Image Processing 2011; 20:2378 – 2386.

[26] Z. Wang, A. C. Bovik, H. R. Sheikh and E. P. Simoncelli. Image Quality Assessment: From Error Visibility to Structural Similarity. IEEE Transactions on Image Processing 2004; 13:1-14.