Cross modality guided liver image enhancement of CT using MRI

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***Abstract*—Low contrast Computed Tomographic (CT) images often hamper the diagnosis of critical tumors found in various human organs. Contrast enhancement schemes play significant role in improving the visualization of these structures. To achieve this objective, Crossmodality Guided Enhancement (CMGE) method is proposed in this paper. The idea is to exploit the diversity of the information extracted from one modality to enhance the important structures including vessels and tumors in another modality. Our method employs information from liver Magnetic Resonance Image (MRI) to generate an enhanced CT image. It entails applying two dimensional histogram specification to map 2D histogram of CT to that of MRI followed by application of top and bottom hat transformations. These morphological operations highlight areas brighter than their surroundings and suppress darker areas. The final image is obtained by combining the results of these operations. Our method is compared with other state of the art contrast enhancement methods both visually and in terms of quality assessment metrics IEM and EME. The results show that our method performs better than these methods. CMGE technique yields improved contrast in low contrast CT images of the human liver and highlights tumors and vessels.**

***Index Terms*—2D histogram specification, top hat, bottom hat transform, contrast enhancement**

I. Introduction

Image enhancement is widely used in the field of medical imaging [1], [7], [9], [11]. Undesired noise, poor contrast, illumination variations and other artifacts are often introduced while acquiring medical images including CT, MRI and US. Surgical outcomes are greatly enhanced after the integration of image guidance techniques with surgical procedures. The undesired image artifacts limit the efficiency of image guidance techniques [3]. However, image enhancement techniques are extremely useful in streamlining the planning and navigation phases. They improve visualization of liver and its internal anatomy to help doctors better diagnose existence of liver tumor and plan intervention accordingly. Moreover, they make subsequent image-based navigation tasks such as registration, feature extraction and segmentation more robust [25].

Computed tomographic imaging is regarded as a primary tool in diagnosis of various human diseases. However, low contrast and imprecise visualization are the drawbacks that limit its utility. CT is frequently preferred over other modalities owing to its quick acquisition time, better ability to capture bony structures and low cost. Keeping human liver into consideration, few structures such as tumors can be better visualized in MR image, while certain vessels are clearly visible in CT. Better diagnosis can be done if information from multiple imaging modalities can be combined in a certain way to get an enhanced image. However, there are few published works on the combination of multiple modalities in the design of guided contrast enhancement methods [4], [5], [9], [10].

The paper is organized as follows. First, we present the review of the recent contrast enhancement approaches. Then, we present our proposed technique. Afterwards, we discuss our results and present comparison with few existing methods. Finally, conclusion is presented.

II. Related Work

Several image enhancement methods have been proposed in the literature including spatial domain [2], [4], [6] and transform domain methods [1], [11]. Wavelet based approaches decompose the image into different scales. In transform based approach, the image is first decomposed into spatial frequency components. Then each component is processed in order to adapt the energy amplification to its spatial frequency content. Wavelet-based methods have been proved to provide better contrast enhancement than other transform based methods. Moreover, wavelet decomposition offers the possibility to denoise the signal and enhance selectively the contrast simultaneously [30], [31]. Another scheme calculates enhancement parameters according to local dispersion of wavelet coefficients [11]. Recently, multimodal image enhancement techniques have been proposed [4], [5] in the context of natural images; these methods denoise an image using its clean counterpart. To propose a cross modality guided denoising scheme is challenging, however, contents in the natural images used under the abovementioned schemes are exactly same, and both images are perfectly registered. Moreover, a pixel level fusion scheme could be used in order to simplify the enhancement process [4], [21]. One of the earlier attempts to use Near Infra-Red (NIR) images for enhancing visible photographs exploited their similar statistical characteristics [4]. The authors used histogram matching in gradient domain to transfer NIR contrast to target image and wavelet coefficients for passing texture information. Nevertheless, the method fails for low light images. Jiang et. al. used dark channel prior model to improve perceptual quality of videos taken at night [22].

Another scheme uses dark flashed infrared noise free image to denoise the corresponding color image. A scale map [9] based on anisotropic filter is constructed and iteratively updated using information from both input images. However, the single image denoising method outperforms this method in case a structure is missing in the guidance image but exists in input image. Zhuo et. al. [4] presented denoising and detail enhancement approach for low light images using near infrared flash image. Shen et. al. calculated [5] patch wise cross correlation between two multimodal images, then applied joint filtering based on least square regression. A promising approach for image processing called "guided image filtering" has been introduced in [38]. Guided image enhancement approach offers the potential to enhance the perceptual quality of an input image by exploiting another image with the similar content or similar intensity distribution [4], [5], [9]. The guidance based image enhancement methods have successfully been applied to denoising and contrast enhancement problems in context of natural images [10], [16].

Recently, deep learning [10] has been applied to crossmodality guided image denoising and claims to generate better results than many existing techniques. The authors use three layer convolution neural networks. The method yields better results than their existing counterparts; however, it performs bad in transferring small structures from guidance map because of confusion with noise components. Wolterink et. al. [23] presented Generative Adversarial Networks for single modality denoising in low dose CT scans.

A gamma correction based optimization approach was proposed for medical image enhancement that minimizes the homogeneity of cooccurrence matrix of the image [6]. However, this approach does not exploit neither the inter-pixel correlation nor the spatial distribution of the local features. Morphological based image enhancement approach is another alternative solution [8]. They have also been applied to enhance vessels in angiography images [2]. Various organs appear at varying depths when medical image is acquired. Keeping in view that every organ possess unlike structure and texture, morphological filters may serve as a useful tool to improve visualization of the structure of interest by introducing sufficient contrast among the neighboring structures [8], [18]. The authors used morphological top hat and bottom hat transform to generate various images with several degrees of enhancement [8].

Another traditional contrast enhancement approach, histogram specification improves contrast of image by manipulating the intensity levels of pixels without taking into account the intensity values of its neighbouring pixels [15]. Two dimensional histogram processing schemes have been proposed recently claiming improvements over their 1D counterparts [12]–[14]. Two dimensional histogram gives the count of pairwise occurrence of every pixel pair existing in the image. It obtains a two dimensional CDF of the input and target images. One such approach uses 1D CDF to map input histogram, therefore, the 2D histogram of output image is considerably divergent from the target histogram. In order to keep 2D histogram of input image close to the target histogram, the difference in intensity values among adjacent pixels are mapped according to the 2D CDF derived from target histogram.

Inspired by the idea of 2DHE, 2D histogram specification has been recently proposed, where the target histogram is derived from a 2D uniform distribution [12]–[14]. The motivation behind the proposed scheme is to exploit contextual information existing among the pixels. The idea of 2D histogram processing has also been applied to video contrast enhancement [13]. It exploits the inter-frame spatial and temporal information.

Another variant of HE called CLAHE has also been applied to enhancement of mammograms [24]. In the context of medical image enhancement, histogram equalization has not been very effective [17]. Although, it redistributes the dynamic range of images that enhances low contrast areas in the image but at the same time introduces unpleasant effects in the resultant images. The quantity of pixels that are low in number is artificially increased which introduces uneven brightness in certain areas. These artificially enhanced images are sometimes pleasant for visual perception specially natural images, however, many significant and fine details may be lost in the medical images. The motive in medical image enhancement is to make certain structures like contours, tumors and vessels visible; the vessel and tumor segmentation algorithms work better on enhanced images compared to original images. Therefore, there is a need to devise contrast enhancement techniques for medical images that do not blindly redistribute the dynamic range but also ensure to keep fine details intact and preserve the spatial coherence of pixels [32].

III. Proposed Method

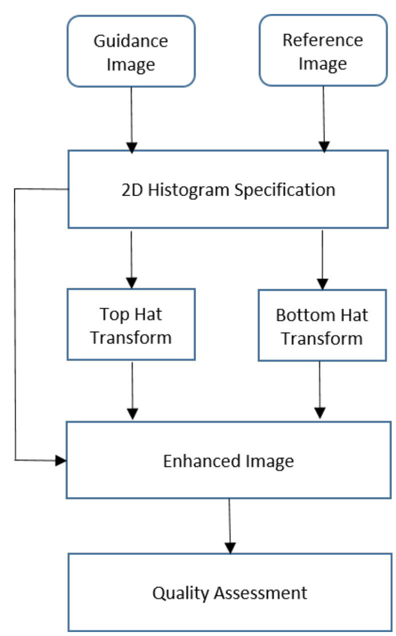


Fig. 1. Proposed Method

The main idea of the proposed method is to adapt the guided image filtering concept to the cross-modality context for medical image enhancement. The idea behind employing guided image processing in the medical imaging context is to exploit the diversity and the complementary information conveyed by the different modalities in order to highlight salient features for facilitating the medical diagnosis. To the best of our knowledge, the idea to use information from cross modal image has not been applied to medical images. The proposed method, Cross Modality Guided Enhancement (CMGE), is based on the same idea to medical images. Through the obtained results, we show that the CT image enhanced using multimodality guidance based framework increases the visibility of the structures of interest, highlights them by amplifying the contrast among various areas and enhance fine details of liver anatomy. Moreover, we show that this strategy works better than the methods that do not incorporate multimodal guidance. This guided image quality enhancement scheme is realized by combining two dimensional histogram based method and morphological-based image processing.

The motivation of using 2D histogram specification is to improve the global contrast of the image by exploiting the inter-pixel correlation. The morphological part of the process consists of top hat and bottom hat transforms. Top hat transform highlights bright areas in the image than their surroundings, while bottom hat transform highlights darker areas. Figure 1 shows the pipeline of the proposed method. First, guidance and input/ reference image that is liver MR image and liver CT images respectively are taken. Two dimensional histogram of input image is mapped to 2D histogram of the guidance image. Then, the image from top hat transform is added to the histogram-matched image and the bottom hat transformed image is subtracted from the resultant to generate the final enhanced image. Quality assessment metrics IEM and EME are used to evaluate the performance of the proposed contrast enhancement method. These metrics have been proven consistent with human judgment of contrast enhancement quality [34]–[36].

A. 2D Histogram Specification

Let f(m,n) denotes the input image signal at pixel (m,n), the associated 2D histogram is defined as below:

$$h_I(c,d) = \sum_{\forall m,n} \sum_{\forall k,l} \lambda_{c,d}(f(m,n), f(k,l)) \tag{1}$$

where

$$\lambda_{c,d}(r,s) = \begin{cases} 1, & \text{if r=c and s=d} \\ 0, & \text{otherwise} \end{cases}$$

$h_I(c,d)$ is normalized as shown:

$$h_I(c,d) = \frac{h_I(c,d)}{\sum_{a,b} h_I(a,b)} \tag{2}$$

c, d, a and b represent pixel values while (m,n) and (k,l) indicate the pixel coordinates. h_G here represents the target 2D histogram, which in our case is that of MR image.

Suppose C_I and C_G represent the 2D cumulative distribution function (CDF) of input and guidance images respectively [12].

$$C_I(a,b) = \sum_{c=0}^{a} \sum_{d=0}^{b} h_I(c,d) \tag{3}$$

$$C_G(a,b) = \sum_{c=0}^{a} \sum_{d=0}^{b} h_G(c,d) \tag{4}$$

The pixel value mapping is expressed as:

$$T(c,d) = \arg\min_{[a,b]} |C_I(c,d) - C_G(a,b)| + \eta(|c-a| + |d-b|) \tag{5}$$

The algorithm searches for T(c,d)= $[T(c,d)_1, T(c,d)_2]$, the target pixel value, where $T(c,d)_1, T(c,d)_2$ indicate pixel values corresponding to c and d. The second term in the above expression selects a closer pixel pair if difference of first term among candidate pixel pairs are very small. At this point, a target pixel value pair is calculated for each input pixel value pair. Now, each pixel is paired with every pixel in its neighborhood, therefore, a relaxed solution is presented to obtain the output pixel value f(m,n). Each adjacent pixel in the neighborhood casts a vote for target pixel value of f(m,n). The value that gives the minimum sum of absolute difference of votes is taken as target pixel value. Practically, it is the median of pixel values voted by adjacent pixels. Using 2D CDF manipulation, target pixel value pair is calculated for each input pixel value pair.

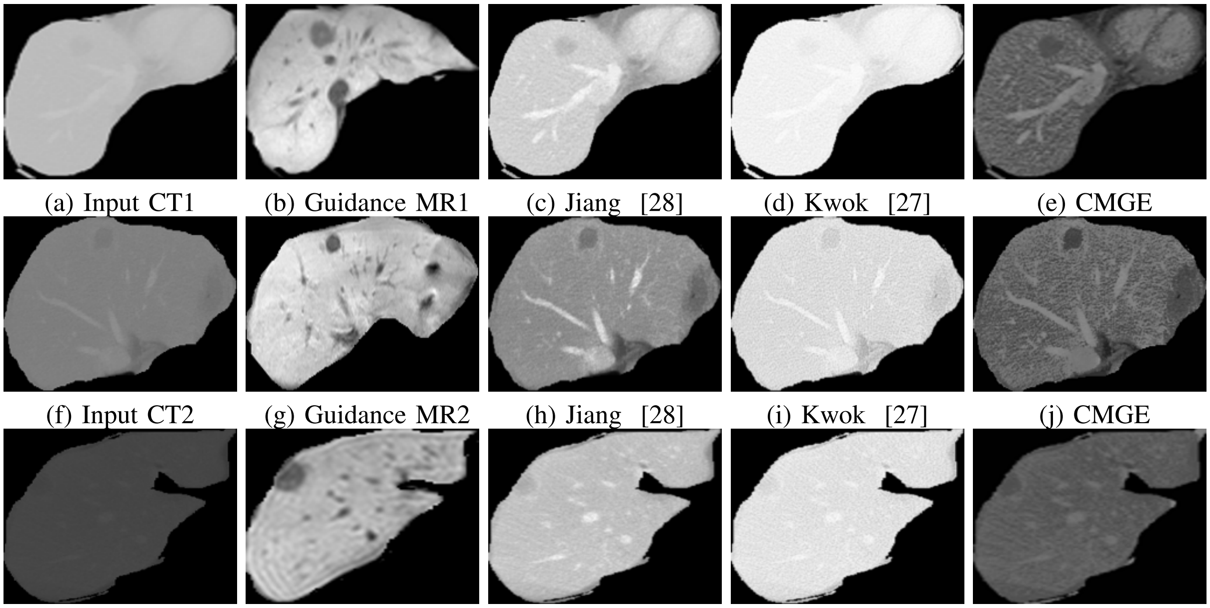
$$f_\star(m,n) = \arg\min_a \sum_{\forall k,l} |a - T(f(m,n), f(k,l))_1| \tag{6}$$

B. Morphological Transforms

Morphological approaches generally exploit structural characteristics of the objects in image [26]. These methods are nonlinear in nature and works by sliding a Structuring Element (SE) over the whole image. Morphological transforms use mathematical relation between categories to obtain specific components of the image that are suitable in describing shape of regions. Among many shapes of the structuring elements, disk shape SE is preferred for enhancing medical images because of their rotation invariance characteristics. Disk shaped structuring element of size 9x9 has been used in this work.

Morphological opening eliminates negligible details from the image where structuring element does not fit in. It yields background of image. Subtracting opening of image from the image itself eradicates the background of image as is done in top hat transform. Closing is supposed to fill selective areas in background of image. Bottom hat transform leaves few dark parts in image where SE is not completely enclosed since it subtracts the image from its closing.

Top hat transform is used in this work since this transform extracts the brighter features in an image, vessels for instance in case of CT images [8]. The top hat transform behaves as a high pass filter and highlights the objects in image that are smaller than the mask. Similarly, bottom hat transform leaves



(a) Input CT1 (b) Guidance MR1 (c) Jiang [28] (d) Kwok [27] (e) CMGE
(f) Input CT2 (g) Guidance MR2 (h) Jiang [28] (i) Kwok [27] (j) CMGE
(k) Input CT3 (l) Guidance MR3 (m) Jiang [28] (n) Kwok [27] (o) CMGE

Fig. 2. Visual comparison of our method against state of the art methods

darker objects in the image [8]. The ultimate effect of applying both operations is that top hat highlights brighter areas and bottom hat transform emphasizes the appearance of dark areas in an image.

At this point in our method, the bright areas can be added to histogram matched image (the outcome of top hat transform) and dark areas (outcome of bottom hat transform) subtracted from the image. The effect of this step is that ample contrast is introduced between different organs in our image.

C. Enhancement

The image after 2D histogram specification I_h, is added to the image obtained after top hat transform I_{TH}. The image after bottom hat transformation I_{BH} is subtracted from the resultant to get the final enhanced image represented by I_e. The enhancement process can be mathematically written as:

$$I_e = I_h + I_{TH} - I_{BH} \quad (7)$$

The proposed CMGE method combines 2D histogram specification with morphological transforms. The rationale of combining these two methods is that 2D histogram specification alone cannot bring the desired results in enhancing images specially medical images. Since it is global enhancement technique and the histogram of resultant image deviates largely from target histogram, we need to either optimize the enhancement process or apply another enhancement mechanism. Morphological operations are simple but at the same time offer strong potential in introducing contrast among different regions in medical images without complicating the overall process. One of the optimization based enhancement methods use Retinex model with spatially adaptive l_2 norm [37]. The method generates an adaptive map that assigns weights to pixels based on brightness and local variance.

Our work is the first one to apply the concept of cross modal guidance to medical images. This is a computationally simple method that does not necessitate any parameter tuning. We believe that it can serve as a basis to propose sophisticated methods that further improve the enhancement outcomes when cross modal guidance is incorporated in the contrast enhancement process.

IV. Experiments

In this section, we present the dataset used in the experiment and the results obtained using the proposed CMGE method. The performance of the proposed method is evaluated in terms of index of quality improvement using two contrast evaluation measures, namely EME and IEM [19], [20], [35]. The obtained results are summarized in tables I and II. Here, the comparison is restricted to three types of image.

A. Dataset

The data for this research work is acquired from Intervention Center, Oslo University Hospital. CT and MR images of the same patient are taken; images are not registered but since we apply global enhancement operations, therefore, registration of input images is not essential. The original MR and CT images were in DICOM format and their intensity values varied significantly. Therefore, both the images were converted to similar intensity range, i.e. 0 to 255, so that processing could be simplified. We tested our method on 40 image pairs (40 CT and 40 MR images). Visual comparison is presented for three images , however, qualitative assessment is done for the whole set of images. The results and analysis are presented in the following section.

B. Results

Figure 2a, f and k show the original CT images and figure 2b, g and l show the corresponding MR (guidance) images. The results of applying proposed CMGE technique are shown in figures e, j and o. Our method is compared with two methods [27], [28]. The authors used the unsharp masking filter together with particle swarm optimization [27] and optimal gamma correction for contrast enhancement [28]. Figures c,h and m are the images obtained after applying the method proposed in [28], while d,i and n obtained after applying [27]. The results show that the tumor and vessels not visible in the original CT images can be clearly seen in the image enhanced by our method. The enhancement results are not good in case of [27]. CMGE can improve visualization of the tumors because of introducing ample contrast. The objective assessment is done in the subsequent section. The surface plot for the input image CT1 is illustrated in figure 3. The tumor and major vessel can be seen discriminated from the liver parenchyma in the plot.

TABLE I
COMPARISON OF OUR METHOD FOR THREE IMAGES

Methods	Input CT 1		Input CT 2		Input CT 3	
	EME	IEM	EME	IEM	EME	IEM
Jiang [28]	1.92	1.56	4.36	2.65	3.15	2.82
Kwok [27]	1.75	1.43	3.024	1.815	3.12	2.52
CMGE	**2.54**	**1.7**	**4.84**	**3.173**	**3.2**	**2.83**

TABLE II
COMPARISON OF OUR METHOD WITH OTHER METHODS

Method	IEM	EME
Jiang [28]	3.82	2.6
Kwok [27]	1.88	1.4
CMGE	**4.11**	**4.3**

V. CONTRAST ENHANCEMENT EVALUATION

Contrast enhancement evaluation (CEE) is a difficult and complex task. Indeed, it is a high level task in computer vision and is context dependent [33]. One way to evaluate the quality of the results in an objective and automatic manner is to use quantitative measures. A few CEE metrics, as compared to classical image quality assessment context, have been proposed in the literature. According to the study in [34]–[36], some simple CEE measures have been proven consistent with human judgment of perceptual contrast quality. Here, the enhanced images have been evaluated using two quality assessment measures EME [20] and IEM [19]. For the sake of completeness of the paper, both are mathematically expressed here.

$$IEM = \frac{\sum_{m=1}^{k1}\sum_{l=1}^{k2}\sum_{n=1}^{8}\left|I_{e,c}^{l,m} - I_{e,n}^{l,m}\right|}{\sum_{m=1}^{k1}\sum_{l=1}^{k2}\sum_{n=1}^{8}\left|I_{r,c}^{l,m} - I_{r,n}^{l,m}\right|} \quad (8)$$

IEM is defined as the ratio of sum of absolute values of the difference of each pixel from its 8-neighbors of the enhanced image to the guidance image. The image is divided into blocks of size k_1, k_2. $I_{e,c}^{l,m}$ and $I_{r,c}^{l,m}$ represent the value of centre pixel in *(l,m)* block for enhanced and input image respectively. n=1,..8 are the 8 neighbors of centre pixel. EME [20] is expressed as:

$$EME = \frac{1}{k_1 k_2}\sum_{m=1}^{k1}\sum_{l=1}^{k2} 20\ln\left(\frac{I_{max}^{l,m}}{I_{min}^{l,m}}\right) \quad (9)$$

$I_{max}^{l,m}$ and $I_{min}^{l,m}$ refer to maximum and minimum intensity values in the enhanced image.

The quantitative results are given in table I for the three images separately; table II presents the overall results for the complete set of images. We get the IEM value of 1.7, 3.173 and 2.83 for the three input CT images in case of the CMGE method which are better than the IEM values obtained for the other two approaches. Similarly for the EME metric, we obtain better values for proposed method as mentioned in table I.

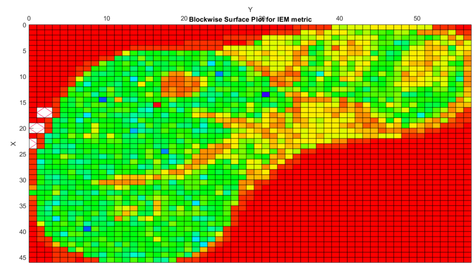


Fig. 3. Surface Plot

VI. CONCLUSION

In this study a novel method to improve contrast of liver for cross-modal images (CT images and MR images) using 2D histogram specification and morphological transforms has been proposed. We have shown that an efficient method for contrast enhancement in the medical imaging context could be designed by combining image guided enhancement approach with some classical image processing operators. Through the obtained results, it is clearly shown that the proposed CMGE technique significantly enhances the contrast making the discrimination between tumor and liver parenchyma easier. In this study, the comparison of our method has been restricted to some similar methods of the state of the art. It is demonstrated that CMGE outperforms these methods. In the future, we intend to extend our method to handle more complex types of tumors in liver CT images. The other direction to be explored in a near future is combine the developed ideas with a machine learning based approach.

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REFERENCES

[1] Yang, Y., Z. Su, and L. Sun. "Medical image enhancement algorithm based on wavelet transform." Electronics letters 46.2 (2010): 120-121.

[2] Sun, K. Q., and N. Sang. "Morphological enhancement of vascular angiogram with multiscale detected by Gabor filters." Electronics Letters 44.2 (2008): 86-87.

[3] Cleary, Kevin, and Terry M. Peters. "Image-guided interventions: technology review and clinical applications." Annual review of biomedical engineering 12 (2010): 119-142.

[4] Zhuo, Shaojie, et al. "Enhancing low light images using near infrared flash images." 2010 IEEE International Conference on Image Processing. IEEE, 2010.

[5] Shen, Xiaoyong, et al. "Mutual-structure for joint filtering." Proceedings of the IEEE International Conference on Computer Vision. 2015.

[6] Amiri, S. Asadi, and H. Hassanpour. "A preprocessing approach for image analysis using gamma correction." International Journal of Computer Applications 38.12 (2012): 38-46.

[7] Mahmoud, Tarek A., and Stephen Marshall. "Medical image enhancement using threshold decomposition driven adaptive morphological filter." 2008 16th European Signal Processing Conference. IEEE, 2008.

[8] Hassanpour, Hamid, Najmeh Samadiani, and SM Mahdi Salehi. "Using morphological transforms to enhance the contrast of medical images." The Egyptian Journal of Radiology and Nuclear Medicine 46.2 (2015): 481-489.

[9] Yan, Qiong, et al. "Cross-field joint image restoration via scale map." Proceedings of the IEEE International Conference on Computer Vision. 2013.

[10] Li, Yijun, et al. "Deep joint image filtering." European Conference on Computer Vision. Springer, Cham, 2016.

[11] Łoza, Artur, et al. "Automatic contrast enhancement of low-light images based on local statistics of wavelet coefficients." Digital Signal Processing 23.6 (2013): 1856-1866.

[12] Jung, Seung-Won. "Two-dimensional histogram specification using two-dimensional cumulative distribution function." Electronics Letters 50.12 (2014): 872-874.

[13] Celik, Turgay. "Spatio-temporal video contrast enhancement." IET Image Processing 7.6 (2013): 543-555.

[14] Celik, Turgay. "Two-dimensional histogram equalization and contrast enhancement." Pattern Recognition 45.10 (2012): 3810-3824.

[15] Gonzalez, Rafael C., and Richard E. Woods. "Digital image processing." (2002).

[16] He, Kaiming, Jian Sun, and Xiaoou Tang. "Guided image filtering." IEEE transactions on pattern analysis and machine intelligence 35.6 (2012): 1397-1409.

[17] Wang, Qian, Liya Chen, and Dinggang Shen. "Fast histogram equalization for medical image enhancement." 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, 2008.

[18] Mahmoud, Tarek A., and Stephen Marshall. "Medical image enhancement using threshold decomposition driven adaptive morphological filter." 2008 16th European Signal Processing Conference. IEEE, 2008.

[19] Jaya, V. L., and R. Gopikakumari. "IEM: a new image enhancement metric for contrast and sharpness measurements." International Journal of Computer Applications 79.9 (2013).

[20] Agaian, Sos S., Karen Panetta, and Artyom M. Grigoryan. "A new measure of image enhancement." IASTED International Conference on Signal Processing Communication. 2000.

[21] Zhang, Xiaopeng, Terence Sim, and Xiaoping Miao. "Enhancing photographs with near infra-red images." 2008 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2008.

[22] Jiang, Xuesong, et al. "Night video enhancement using improved dark channel prior." 2013 IEEE International Conference on Image Processing. IEEE, 2013.

[23] Wolterink, Jelmer M., et al. "Generative adversarial networks for noise reduction in low-dose CT." IEEE transactions on medical imaging 36.12 (2017): 2536-2545.

[24] Pisano, Etta D., et al. "Contrast limited adaptive histogram equalization image processing to improve the detection of simulated spiculations in dense mammograms." Journal of Digital imaging 11.4 (1998): 193.

[25] Dhanachandra, Nameirakpam, Khumanthem Manglem, and Yambem Jina Chanu. "Image segmentation using K-means clustering algorithm and subtractive clustering algorithm." Procedia Computer Science 54 (2015): 764-771.

[26] Serra, Jean. Image analysis and mathematical morphology. Academic Press, Inc., 1983.

[27] Kwok, Ngaiming, and Haiyan Shi. "Design of unsharp masking filter kernel and gain using particle swarm optimization." 2014 7th International Congress on Image and Signal Processing. IEEE, 2014.

[28] Jiang, G., et al. "Image contrast enhancement with brightness preservation using an optimal gamma correction and weighted sum approach." Journal of Modern Optics 62.7 (2015): 536-547

[29] Heijmans, Henk JAM. Morphological image operators. Vol. 4. Boston: Academic Press, 1994.

[30] Cherifi, D., Azeddine Beghdadi, and A. H. Belbachir. "Color contrast enhancement method using steerable pyramid transform." Signal, Image and Video Processing 4.2 (2010): 247-262.

[31] Sdiri, Bilel, et al. "Efficient enhancement of stereo endoscopic images based on joint wavelet decomposition and binocular combination." IEEE transactions on medical imaging 38.1 (2018): 33-45.

[32] Wang, Shuhang, et al. "Naturalness preserved enhancement algorithm for non-uniform illumination images." IEEE Transactions on Image Processing 22.9 (2013): 3538-3548.

[33] Le Négrate, Alain, Azeddine Beghdadi, and Henri Dupoisot. "An image enhancement technique and its evaluation through bimodality analysis." CVGIP: Graphical Models and Image Processing 54.1 (1992): 13-22.

[34] Qureshi, Muhammad Ali, Azeddine Beghdadi, and Mohamed Deriche. "Towards the design of a consistent image contrast enhancement evaluation measure." Signal Processing: Image Communication 58 (2017): 212-227.

[35] Qureshi, Muhammad Ali, et al. "A comprehensive performance evaluation of objective quality metrics for contrast enhancement techniques." 2016 6th European Workshop on Visual Information Processing (EUVIP). IEEE, 2016.

[36] Beghdadi, Azeddine, M. Ali Qureshi, and M. Deriche. "A critical look to some contrast enhancement evaluation measures." 2015 Colour and Visual Computing Symposium (CVCS). IEEE, 2015.

[37] Park, Seonhee, et al. "Low-light image enhancement using variational optimization-based retinex model." IEEE Transactions on Consumer Electronics 63.2 (2017): 178-184.

[38] CHe, Kaiming, Jian Sun, and Xiaoou Tang. "Guided image filtering." European conference on computer vision. Springer, Berlin, Heidelberg, 2010.