Two-Stage Contrast Enhancement Method for Liver Tumor Segmentation

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***Abstract*—** Tumor segmentation in Computed Tomography (CT) images is a crucial step in image-guided surgery. However, low-contrast CT images impede the performance of subsequent segmentation tasks. Contrast enhancement is then used as a preprocessing step to highlight the relevant structures, thus facilitating not only medical diagnosis but also image segmentation with higher accuracy. The proposed method is based on two concepts, namely adaptive gamma correction using DWT-SVD and OPTimized Guided Contrast Enhancement (OPTGCE). In the proposed DWT-SVD scheme, the technique decomposes the input medical image into four frequency sub-bands by using DWT and then estimates the singular value matrix of the LL sub-band image. An enhanced LL component is generated using an adequate correction factor and inverse SVD. The proposed OPTimized Guided Contrast Enhancement (OPTGCE) scheme exploits both contextual information from the guidance image and structural information from the input image. Tumor segmentation algorithm is applied on the enhanced images to analyze the performance of the proposed method in facilitating tumor segmentation. The qualitative and quantitative analysis using metrics including entropy, MCCEE, and MIGLCM shows the superiority of the proposed method in comparison with the existing methods that do not include guidance mechanism

Keywords—: *2D-DWT, Gamma Correction, SSIM, Gradient.*

I. INTRODUCTION

Liver cancer is the fifth most prevalent cancer in the world, carrying a low survival rate. Nevertheless, timely detection of cancerous tumors and effective treatment strategies can improve the overall survival rate. Diagnostic imaging techniques such as CT facilitate timely diagnosis of cancer; however, low contrast and noise limit their utility. Moreover, such low-contrast images make segmentation and tumor detection challenging problems that can be overcome by applying a contrast enhancement beforehand.

It is also worth mentioning here that a single medical imaging modality is unable to capture all the relevant structural information from the organs. For this reason, it is now becoming more common to acquire both CT and MR images periodically during liver cancer diagnosis and treatment. Therefore, it would be interesting to use the additional captured information from one imaging modality (e.g. MRI) to enhance the other (e.g. CT). The concept of enhancing the image from one modality using cross-modal image information is not novel; similar ideas have been successfully applied to natural images. One such approach for liver CT image enhancement using the corresponding MR images was proposed to improve the visibility of tumors and vessels. In general, the cross-modality guided enhancement methods have shown better performance in comparison with the classic single image enhancement methods.

Currently, there are two main challenges related to image enhancement in the medical context. Firstly, most recent enhancement techniques are tailored to only specific types of images. Secondly, it is not easy to find a well-established benchmark for evaluating the existing enhancement methods. For these reasons, the effectiveness of the enhancement approaches is often assessed based on their impact on the underlying application. For medical imaging, the motivation of CE, in general, is to improve the visual appearance of relevant organ structures for better diagnosis and intervention. However, limited research has been done on image quality enhancement to improve the segmentation of such organ structures. By using CE as preprocessing step, improved segmentation of relevant structures in CT images could be achieved as concluded. Therefore, there is a dire need for efficient CE algorithms for such images.

Traditional enhancement methods suffer from limitations such as saturation, over-enhancement, and uneven contrast spatial distribution, that may result from the uncontrolled CE process. One way to overcome such limitations is to combine the contrast enhancement approach with a quality control scheme. Inspired by the guided filtering approach and the

simplicity of context-aware histogram-based image quality enhancement, propose in this project a two stage contrast enhancement technique to improve the contrast of liver CT images using MRI images as guiding input data.

The main contributions of this paper are:

- To design a goal-oriented contrast enhancement method to improve tumor segmentation
- Proposed approach is principally based on adaptive gamma correction using DWT with SVD
- The two-dimensional histogram specification-based CE process is formulated as an optimization problem and extended to multi-modal medical imaging data for the first time
- SSIM gradient is incorporated in the optimized cross-modality guided 2D-HS framework to preserve structural fidelity of the enhanced image with the original image while applying enhancement
- In order to obtain the objective of contrast enhancement without affecting the important structures of the image, the algorithm achieves a nice balance between retaining structural similarity with input image (by integrating SSIM gradient) and enhancing contrast by employing 2D entropy. The suggested combination of cross-modal guidance and quality control enhances the CT image exploiting contextual information, as opposed to context-unaware schemes.
- A new goal-oriented performance evaluation of the proposed approach is done utilizing objective quality metrics and through segmentation results applied on real multi-modal liver data. Comparison with single enhancement techniques validate the superior performance of the proposed method

The rest of the paper is organized as follows. Section II provides a brief review of relevant contrast enhancement methods. Section III describes the proposed Gamma correction and Optimized guided CE method. Experimental results of CE are discussed in section IV. The results of applying segmentation on the enhanced images are described in section V, followed by conclusion in section VI.

II. RELATED WORKS

Due to the intrinsic endoscopic domain characteristics and the surgical exercise, stereo endoscopic images may suffer from different degradations which affect its quality. In this paper two joint enhancement methods [1] which operate in the wavelet transform domain. More precisely, by resorting to a joint wavelet decomposition, the wavelet subbands of the right and left views are simultaneously processed to exploit the binocular vision properties.

Survey examination in patients with a known extra-hepatic malignancy to exclude the presence of hepatic and extra-hepatic involvement is normally undertaken with a contrast-enhanced computed tomography examination. When patients with hepatic metastases are being considered for metastasesectomy, they undergo a staging examination [2] with contrast-enhanced magnetic resonance imaging (MRI) using tissue-specific contrast agents. Patients with chronic liver disease who are at risk for hepatocellular carcinoma undergo periodic liver screening for focal liver detection, usually with ultrasonography (US) with MRI being used when US is equivocal.

The presented method can extract the edges of an image accurately and enhance them while preserving smooth areas and weak textures; these improvements can be particularly helpful to doctors' diagnoses. The primary contribution of this paper is the [3] Adaptive Fractional Differential Algorithm (AFDA), which uses the improved Otsu algorithm to segment the edges, textures and smooth areas of images. This algorithm allows the optimal fractional order of each pixel to be obtained using an adaptive fractional differential function constructed based on the area feature of image. As a result, the image can be enhanced adaptively.

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 [4] 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.

To mitigate the content-blindness, a family of filters, called joint/guided filters, have attracted a great amount of attention from the community. The main drawback of most joint/guided filters comes from the ignorance of structural inconsistency between the reference and target signals like color, infrared, and depth images captured under different conditions [5]. The proposed muGIF is very flexible, which can work in various modes including dynamic only, static/dynamic and

dynamic/dynamic modes. Although the objective of muGIF is in nature non-convex, by subtly decomposing the objective, we can solve it effectively and efficiently.

We propose a two-image restoration framework [6] considering input images in different fields. The major issue in such a framework is to handle structure divergence and find commonly usable edges and smooth transition for visually compelling image reconstruction. We introduce a scale map as a competent representation to explicitly model derivative-level confidence and propose new functions and a numerical solver to effectively infer it following new structural observations.

The novelties of the proposed algorithm consist of tuning the standard single-scale Retinex, [7] adding a normalized-ameliorated Sigmoid function and adapting some parameters to improve its enhancement ability. The proposed algorithm is tested with synthetically and naturally degraded low-contrast CT images, and its performance is also verified with contemporary enhancement techniques using two prevalent quality evaluation metrics-SSIM and UIQI.

An ameliorated version of the contrast-limited adaptive histogram equalization (CLAHE) is introduced in this article to provide a good brightness with decent contrast for CT images [8]. The novel modification to the aforesaid technique is done by adding an initial phase of a normalized gamma correction function that helps in adjusting the gamma of the processed image to avoid the common errors of the basic CLAHE of the excess brightness and imperfect contrast it produces.

We propose persistence and grid-stride loop based fast parallel contrast enhancement for CT liver images. We use enhanced CT liver image for the lesion or tumor segmentation. We implement the fast parallel gradient based dynamic seeded region growing for lesion segmentation [9].

We observe that abundant blood vessels are available on tissue surfaces and can be extracted as a new set of image features. In this paper, two types of blood vessel features are proposed for endoscopic images: branching points and branching segments [10]. Two novel methods, ridgeness-based circle test and ridgeness-based branching segment detection are presented to extract branching points and branching segments, respectively.

III PROPOSED SYSTEM

Two-stage low contrast liver enhancement based on adaptive gamma correction and OPTGCE are proposed. In a first step, the technique decomposes the input image into four frequency sub-bands by using DWT. Then, estimates the singular value matrix of the LL sub-band image. In a second step, an enhanced LL component is generated using an adaptive gamma correction and inverse SVD. Finally, inverse DWT together with the unprocessed sub-bands for first stage enhanced image generation. The main advantage of such a dynamic method is that it could be applied to large types of images for contrast enhancement with simultaneously preserving the edge information of the original image. In fact, the SVD technique is applied in a first step for contrast enhancement of LL sub-band image obtained using DWT. In a second step, for a further contrast improvement, the obtained LL sub-band image is processed using a modified transfer function based on adaptive gamma correction transformation. Parameters of gamma transformation are dynamically and automatically calculated depending on the statistical information of the processed LL sub-band image. In the next step, propose a similar approach for medical images using cross-modal information. The new CE approach is hence based on two concepts, namely, crossmodality-guided medical image enhancement to improve the global contrast, and quality control to preserve the local structures during enhancement. Here, we formulate the cross-modal CE as an optimization problem, where the gradient of structural similarity index measure (SSIM) is used for local structure preservation and minimizing artifacts introduced during enhancement.

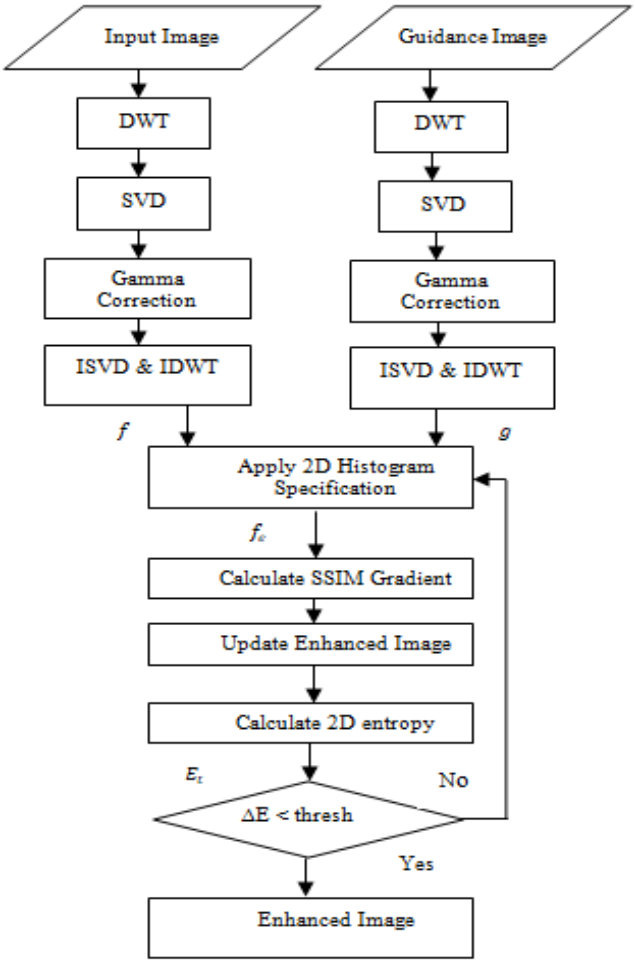


Fig. 1. Block diagram of the proposed method

Generally, classical Contrast Enhancement (CE) methods do not optimize an objective function or contrast-related measure; instead, they manipulate the pixel values according to a predefined distribution. Besides, these approaches amplify the contrast without objectively controlling the possible artifacts that may arise from the CE process. To the best of our knowledge, there are very few works where the contrast enhancement effect is controlled according to a well-defined framework. In this project, a novel two-stage method for low-contrast image enhancement is proposed. It including a adaptive gamma correction using DWT and a OPTGCE is proposed. DWT algorithm is considered to decompose the dark original image into different sub-band images. In order to obtain an improved image characterized by higher contrast with edges preservation, only LL sub-band images are processed using SVD method and adaptive intensity transformation using gamma adjustment function. Parameters of gamma correction are computed dynamically and automatically for each image according to its statistical information.

The proposed method OPTGCE operates according to this strategy. It applies HS-based CE to the low-contrast CT image based on the second-order distribution of an image of a complementary modality, that is MRI. The motivations behind the use of histogram-based methods are essentially their simplicity, reduced computational load, and the fact of exploiting a global statistical quantity that contains essential information on the distribution of pixel values. This is especially advantageous in the case of a large size of medical imaging data. Therefore, the 2D histogram effectively exploits the inter-pixel interactions, i.e. second-order statistics, in the design of the CE scheme. This treatment enhances the overall contrast well but may suffer from some side effects. Indeed, the locally relevant structures of the image can be negatively affected, leading the processed image to be divergent from the original. Therefore, it is necessary to control the critical parameters of the CE process to amplify local contrast while simultaneously preserving the intrinsic structures of the image. One strategy to prevent the CE from side effects is to control the enhancement by using a local similarity measure between the input and enhanced image or some stopping criteria. Here, we perform the optimization using a measure that is directly related to the structural information in the image and carries contrast information. Furthermore, the extent of contrast is quantified through the two-dimensional entropy. The flowchart of the proposed technique is shown in Fig.1.

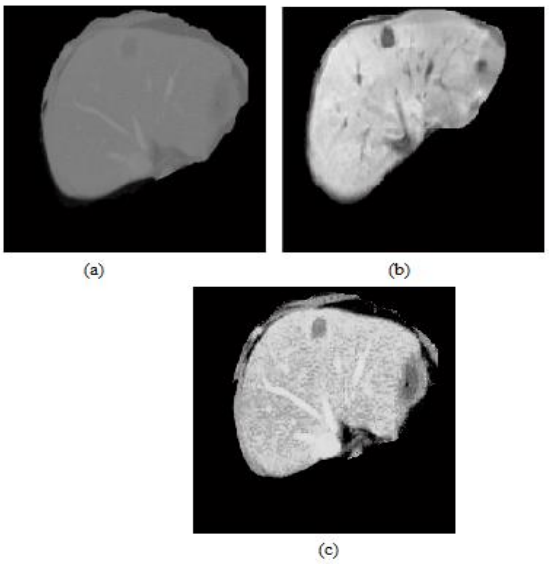


Fig.2 Input Processing (a) Input Image (b) Guidance Image (c) 2D-HS Output

3.1 ADAPTIVE GAMMA CORRECTION

A) DISCRETE WAVELET TRANSFORM

The discrete wavelet transform (DWT) is a powerful implementation of the WT using the dyadic scales and positions. The fundamentals of DWT are introduced as follows. Suppose x(t) is a square-integral function, then the continuous WT of x(t) relative to a given wavelet ψ(t) is defined as

$$W_\psi(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt$$

Where

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{b}\right)$$

Here, the wavelet $\psi_{a,b}(t)$ is calculated from the mother wavelet ψ(t) by translation and dilation: a is the dilation factor and b the translation parameter (both real positive numbers). There are several different kinds of wavelets which have gained popularity throughout the development of wavelet analysis. The most important wavelet is the Haar wavelet, which is the simplest one and often the preferred wavelet in a lot of applications.

Equation can be discretized by restraining a and b to a discrete lattice ($a = 2^b$ & $a > 0$) to give the DWT, which can be expressed as follows.

$$ca_{j,k}(n) = DS\left[\sum\nolimits_n x(n)g_j^*(n-2^jk)\right]$$

$$cd_{j,k}(n) = DS\left[\sum\nolimits_n x(n)h_j^*(n-2^jk)\right]$$

Here $ca_{j,k}$ and $cd_{j,k}$ refer to the coefficients of the approximation components and the detail components, respectively. g(n) and h(n) denote for the low-pass filter and high-pass filter, respectively. j and k represent the wavelet scale and translation factors, respectively. DS operator means the downsampling. Itis the fundamental of wavelet decomposes. It decomposes signal x(n) into two signals, the approximation coefficients ca(n) and the detail components cd(n). This procedure is called one-level decompose.

B) SINGULAR VALUE DECOMPOSITION

The singular value matrix is calculated by applying SVD on original image matrix. In fact, a given real matrix I may be decomposed into a product of three matrix, commonly calculated according to equation,

$$I = U_I \Sigma_I V_I^T$$

where, Σ_I is the singular value matrix which is a diagonal matrix, U_I and VI are used as orthogonal matrices and T is transpose operator. The singular value matrix Σ_I includes intensity information of the image, that's why SVD technique is considered for image equalization. The ratio of highest singular value of generated normalized matrix, with mean zero and variance of one, for a particular input image may be calculated according to equation,

$$\xi = \frac{\max \Sigma_{N(\mu=0,VAR=1)}}{\max(\Sigma_I)}$$

where, $\Sigma_{N(\mu=0,\ var=1)}$ is the singular value matrix of the synthetic intensity matrix. These coefficients could be considered for equalized image '$I_{equalized}$' reconstruction according to equation,

$$I_{equalized} = U_I(\xi \Sigma_I)V_I^T$$

3.2 INTENSITY TRANSFORMATION AND GAMMA CORRECTION

The gamma correction transformation is given by the following equation

$$I_{out} = c.I_{in}^{\gamma}$$

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 fact, a set of parameters (γ, c) could produce high performances for some considered images but not for some others. 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. Indeed, authors proposed to classify an original image I into either low-contrast class C_1 or moderate contrast class C_2 according to the contrast of considered image using equation

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

where $D = diff((\mu + 2\sigma), (\mu - 2\sigma))$ 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. According to equation, 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).

A) DARK IMAGES WITH LOW CONTRAST (In C1)

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 $I_{out} = I_{in}$. As a response to this constraint, Rahman et al. show that the value of γ could be calculated using equation

$$\gamma = -\log 2(\sigma)$$

The parameter c is also calculated dynamically for different images according to the nature of the respective image using equation

$$c = \frac{1}{1 + Heaviside(0.5 - \mu).(k - 1)}$$

where k is defined by equation

$$k = I_{in}^{\gamma} + (1 - I_{in}^{\gamma}).\mu^{\gamma}$$

and the Heaviside function is given by equation

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

B) DARK IMAGES WITH MODERATE CONTRAST (In C2)

The intensities of a dark input image from the second class are scattered over the available dynamic range. In this case, Iout and c are calculated similarly using equations. However, the correction factor γ is expressed differently using equation, not to make much stretching of the contrast

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

C) PROPOSED MEDICAL IMAGE ENHANCEMENT ALGORITHM

The general method of the proposed algorithm for medical image enhancement is concerted in different parts described as follows. The dark input medical image *'Ii'* is firstly processed by GHE algorithm in order to compute *'$\hat{I}i$ '*. Both images are decomposed by DWT into LL, LH, HL, and HH for *'Ii'*, and $\widehat{LL}$, $\widehat{LH}$, $\widehat{HL}$ and for '$\hat{I}i$'. Indeed, enlightenment information is surrounded in LL sub-band but the edges are concerted in other sub-bands (i.e., LH, HL, and HH).

Hence, 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 a first enhancement step, SVD method is applied over both low frequency components LL and $\widehat{LL}$ to generate respectively U_L, Σ_L, V_L, and $\widehat{U_L}$, $\widehat{\Sigma_L}$, $\widehat{V_L}$. The maximum element in UL and VL, from LL and the maximum element in $\widehat{U_L}$ and $\widehat{V_L}$ from are respectively calculated to determine the correction factor ξ. The correction factor ξ, the enhanced singular value matrix and the enhanced LL sub-band SVD are respectively calculated using equation

$$\zeta = \frac{\max(\hat{U}_L) + \max(\hat{V}_L)}{\max(U_L) + \max(V_L)}$$

$$\overline{\Sigma}_L = \xi \quad x \quad \hat{\Sigma}_L$$

$$\overline{LL}_{SVD} = \hat{U}_L \quad \overline{\Sigma}_L \quad \hat{V}_L^T$$

After that, the enhanced LL sub-band using SVD approach, $\overline{LL}_{SVD}$ is classified according to equation into either low-contrast class C1 or moderate contrast class C2 depending on

the available contrast of this subband image (μ and σ represent respectively the mean and the standard deviation of the enhanced $\overline{LL}_{SVD}$ sub-band image in this case). An adaptive gamma factor correction is calculated dynamically according to the obtained class: equation is considered for LL sub-band images with low contrast (class C1) and equation for LL sub-band images with moderate contrast (class C2). In a second enhancement step, an adaptive intensity transformation using gamma correction is applied on $\overline{LL}_{SVD}$ sub-band according to equation to generate the final enhanced $\overline{LL}_{\gamma}$ sub-band image.

$$\overline{LL}_{\gamma} = c.\left(\overline{LL}_{SVD}\right)^{\gamma}$$

where c is computed using equation

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

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

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

3.3 OPTIMIZED GUIDED CONTRAST ENHANCEMENT (OPTGCE)

The three essential components of the proposed method, namely the 2D histogram specification-based CE, the structural gradient-based similarity measure, and 2D entropy are described below.

A) 2D HISTOGRAM SPECIFICATION

2D Histogram Specification methods can improve the contrast in an image by increasing the pixel-value differences among the neighbouring pixels. This has the disadvantage of not taking into account the strong spatial correlation of pixels and exploiting it in order to avoid side effects associated with histogram approaches. These limitations have led to the use of higher-order statistics of pixel values and characteristics to develop more efficient methods.

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

$$C_f(i,j) = \sum_{i=0}^{K-1} \sum_{j=0}^{K-1} \delta_{ij}\left(f(m,n), f(p,q)\right), \qquad (1)$$

Here, i and j represent the pixel values and (m, n) and (p, q) represent the image coordinates, K is the total number of grey levels, and $0 \le i, j \le K-1$,

$$\delta_{i,j}(a,b) = \begin{cases} 1, & if \ \ i = a \ and \ j = b \\ 0 & Otherwise \end{cases}$$

The transition probability of grey-levels, i.e. the 2D normalized histogram, is derived from the GLCM as follows:

$$h_f(i,j) = \qquad (2)$$

The 2D-histogram is then used in the $\frac{C_f(i,j)}{\sum_{i=0}^{K-1}\sum_{j=0}^{K-1} C_f(i,j)}$ pixel grey-level mapping process using the histogram specification method as described below. This mapping process is based on the two-dimensional Cumulative Distribution Function (CDF) of the input and guidance images computed as follows.

$$H_f(i,j) = \sum_{i=0}^{K-1}\sum_{j=0}^{K-1} h_f(i,j) \qquad (3)$$

The expression of the 2D-CDF of the guidance image is computed similarly and is represented as Hg. Once the 2D-CDF of both images is computed, the transformation T allowing the mapping between the input signal and the desired signal is obtained as follows:

$$T(i,j) = arg^{min}_{[k,l]} \left| H_f(i,j) - H_g(k,l) \right| + \eta(|i-k| + |j-l|) \qquad (4)$$

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.

$$f_e(m,n) = T\left(f(m,n), f(m,n+1)\right) \qquad (5)$$

From Eq. 5, it can be inferred that transformation of each value in the original image [f] to a new value in the enhanced image [f_e] also depends on its neighboring element. Therefore, unlike the 1D histogram specification which only considers

individual pixel values for calculating the CDFs and ultimately mapping these values, this approach also exploits the contextual information among the pixels. Next, we look at the SSIM gradient approach.

B) GRADIENT BASED STRUCTURAL SIMILARITY MEASURE

The idea is to apply global HS to a low-contrast image driven by an SSIM-based measure to control the enhancement through structural similarity changes between the original image and its enhanced variant. SSIM is a well-established measure to calculate the extent of similarity between two images [13]. Considering one image as a reference, the index provides the quality of the image under analysis in comparison with a reference. SSIM index is calculated between corresponding local blocks in images [A] and [B], after which the average of the values is taken to obtain a single value of SSIM as the overall similarity index. Let us assume that ax and bx represent corresponding blocks x in both images; μax and μbx represent the mean intensity values of ax and bx and the standard deviations are given by σ_{a_x} and σ_{b_x}. C1 and C2 are small numbers greater than 0 to ensure the denominator is not zero. The SSIM between the two blocks ax and bx is then expressed as:

$$SSIM(a_x, b_x) = \frac{(2\mu_{a_x}\mu_{b_x} + C1)(2\sigma_{a_x b_x} + C2)}{(\mu_{a_x}^2 + \mu_{b_x}^2 + C1)(\sigma_{a_x}^2 + \sigma_{b_x}^2 + C2)} \quad (6)$$

Few terms in Eq. 6 are described mathematically a

$$\mu_{a_x} = w * a_x$$

$$\sigma_{a_x b_x} = w * (a_x b_x) - \mu_{a_x}\,\mu_{b_x},$$

$$\sigma_{a_x}^2 = w * a_x^2 - \mu_{a_x}^2$$

where w is 11 × 11 Gaussian kernel and ∗ indicates convolution. Eq. 6 could be regarded as expression for SSIM index map, $SSIM_{map}$ calculated via element wise addition and multiplication using parameters expressed in Eq. 7. Then, at all points, $SSIM_{map}$ indicates local similarity between images [A] and [B]. The global SSIM index for the overall images can then be expressed a

$$SSIM(A, B = \frac{1}{Z}\sum_{\forall x} SSIM_{map}(a_x, b_x; x)$$

where Z denotes the number of pixels in either image.

. For the local SSIM measures in Eq. 6, we define the following terms for compactness.

$$\propto_1 (a_x, b_x) = 2\mu_{a_x}\mu_{b_x} + C1,$$

$$\propto_2 (a_x, b_x) = 2\sigma_{a_x b_x} + C2$$

$$\beta_1(a_x, b_x) = \mu_{a_x}^2 + \mu_{b_x}^2 + C1,$$

$$\beta_1(a_x, b_x) = \sigma_{a_x}^2 + \sigma_{b_x}^2 + C2$$

. Here, 2D-HS is applied to enhance CT images by exploiting the better quality of MR images. When applied in the framework of optimization, the SSIM gradient refines the enhancement process incrementally.

The integration of SSIM ultimately preserves the overall morphology of the original image with minimal information loss during enhancement. Here, we denote the input image as [f] and the image whose structural similarity is being compared with [f] as [f_e]; [f_e] is obtained after applying 2D-HS. Now, to adapt the notion of SSIM gradient to our scenario, let us replace [A] by [f_e] and [B] by [f] and rewrite Eq. 8 as:

$$SSIM(f_e, f) = \frac{1}{Z}\sum_{\forall x} SSIM_{map}(f_{e_x}, f_x; x)$$

Calculating the derivative of Eq. 10 with reference to [fe] gives the SSIM gradient expression as follows:

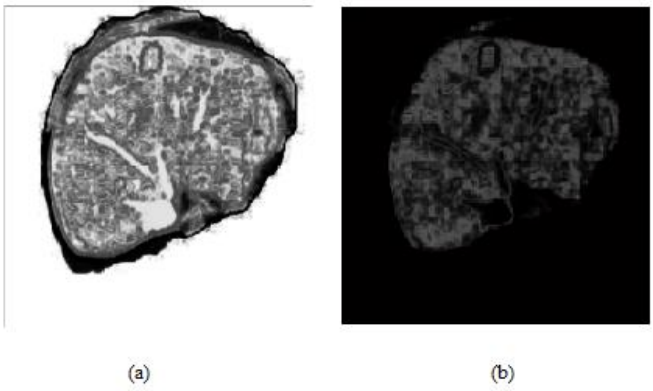
$$\partial_{f_e} SSIM(f_e, f)$$

$$= \frac{2}{Z}\left[\left(w * \frac{\alpha_1}{\beta_1\beta_2}\right) f\right]$$

$$+ \left(w * \frac{-SSIM_{map}}{\beta_2}\right) f_e$$

$$X\left[+w * \frac{\mu_{f_e}(\alpha_2 - \alpha_1) - \mu_f(\beta_2 - \beta_1) SSIM_{map}}{\beta_1\beta_2}\right]$$

where α_1, α_2, β_1 and β_2 have been described in Eq. 9a and 9b.



(a) (b)

Fig.3 SSIM Result. (a) SSIM Image (b) SSIM Gradient Image

C) CONTRAST ENHANCEMENT WITH QUALITY CONTROL

Initially, set the input CT image [f] equal to [f`] and guidance MRI as [g]. The CDFs of [f] and [g] are calculated, the transformation T allowing the mapping between the input signal and the desired signal is obtained. The pixel values in [f`] are mapped to new values to get enhanced image. 2D entropy is used to control the level of enhancement. The stopping criterion is determined by the gain in 2D entropy achieved for the enhanced image

The estimated increase in SSIM at iteration t is mathematically described as

$$\triangle SSIM(t) = \alpha Z \sum_{\forall x} (\partial_{f_e} SSIM(f, f_e(t)))^2$$

Based on the behavior of SSIM(t) at several iterations, 1 SSIM(t) can be modeled by $\alpha r s^t$ [15]. The final value of SSIM (after several iterations) can be expressed as:

$$SSIM_f = SSIM' + \frac{r\alpha Z}{1-s}$$

Proposed experiments show that SSIM value changes faster in earlier iterations, therefore the algorithm is executed three times to calculate the quantities in Eq. 13. Replacing $SSIM_f$ value by 1 (the ideal value) and substituting the above values in Eq. 13, the approximated upper bound on α can be calculated as:

$$SSIM_f = SSIM' + \frac{r\alpha Z}{1-s}$$

Proposed method to measure the contrast enhanced at each iteration by applying 2D-HS. Therefor2D entropy is used to control the level of enhancement. Here, we have used 2D entropy to formulate this criterion a

$$E_t = -\sum_{i=0}^{K-1} \sum_{j=0}^{K-1} h_{f_{e(t)}}(i,j) \ln(h_{f_{e(t)}}(i,j))$$

The change in entropy of the enhanced image gained with every iteration is calculated as follows

$$\triangle E = E_t - E_{t-1}$$

. At a specific point in the optimization process, when 1E becomes negligible (close to zero) or when the 1E value starts oscillating, the enhancement process is stopped

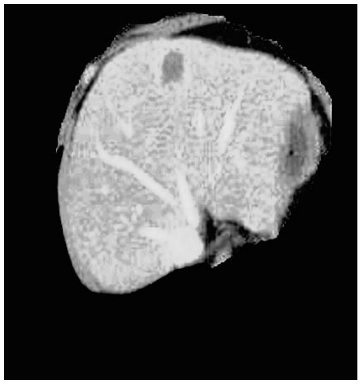


Fig.4 Enhanced Output

IV. PERFORMANCE EVALUATION

The data used in this research work is provided by the Intervention Center, Oslo University Hospital in Norway. Liver CT and MR data of the same patient are used; however, CT-MRI data is not registered since registration is not required for global enhancement methods. Here tested our method on 10 patients' data constituting 12 CT-MR image pairs (containing tumors). The images from different volumes are of different spatial sizes (such as 512 × 512, 360×240) with pixel values in the range [0, 255]. In medical image processing tasks such as segmentation and enhancement, the processing is often restricted to a particular organ and the nearby organs are removed from the medical images. The liver area in the images is therefore separated and processing is applied only to this region.

Image Quality Assessment (IQA) is a well-investigated research field especially in the case of natural images. However, the use of existing IQA metrics has serious limitations in the medical context . The objectives of CE in the medical context are quite different. While in the case of natural images the objective is to measure the effect of various distortions on the perceptual quality of the image; in the medical context even if some degradation may disturb the radiologists the focus is rather on the diagnosis. Therefore, the existing IQA metrics must be used with special care. Another challenging topic is how to evaluate the performance of a given image quality enhancement algorithm in terms of perceptual quality. In the proposed system, focus on some contrast enhancement evaluation (CEE) metrics. The motivation of the OPTGCE is to emphasize the appearance of specific structures in the image and convey the maximum structural information to facilitate tumor segmentation. To this end, we have chosen three different CEE metrics to evaluate the quality of enhanced images. The first metric is a mutual information-based no reference metric called MIGLCM. This

metric offers quantitative criteria that examines the changes in the statistical features, joint entropy, and mutual information, acquired from the GLCM of the original and the enhanced images. Besides MIGLCM, we have used a recent metric Multi-Criteria Contrast Enhancement

Table 1.1 Quantitative assessment of different enhancement methods.

Image	Entropy			MIGLCM		
	CMGE	OPTGCE	Proposed	CMGE	OPTGCE	Proposed
1	2.32	3.05	**4.2**	1	1.1	**3.2**
2	1.7	1.9	**2.1**	0.93	1.05	**4.7**
3	1.52	2.1	**3.5**	0.82	0.95	**2.80**
4	1.11	1.88	**2.70**	0.64	0.82	**2.75**

For the last metric, have used entropy, which is often used in QA of medical image enhancement . Table 1.1 lists the median values of MIGLCM and entropy. A higher value of MIGLCM reflects better performance of CE algorithms. Besides, higher entropy values also correspond to superior CE performance; however, there is no specified range for this metric. From the tabular results, we can observe that OPTGCE demonstrates the best performance. For MCCEE and entropy, Cross-Modality Guidance-based enhancement (CMGE) and Histogram Equalization with Maximum Intensity Coverage(HEMIC) are ranked low overall by the two QA metrics.

V. TOWARDS AN OPTIMAL SEGMENTATION PRESERVING LOCAL STRUCTURES

The results of applying gradient-driven SRG algorithm on enhanced as well as input images are demonstrated in Fig. 5. In general, application of the CE methods improve the contrast of the input image, which ultimately enables SRG to locate tumor contours favorably. However, OPTGCE well preserves uniformity in the structure of tumors in the enhanced image together with yielding sharp tumor edges. Therefore, Seeded Region Growing (SRG) algorithm is better able to locate the tumor contours in the OPTGCE-enhanced images. This property enables OPTGCE to outperform other CE methods in facilitating tumor segmentation.

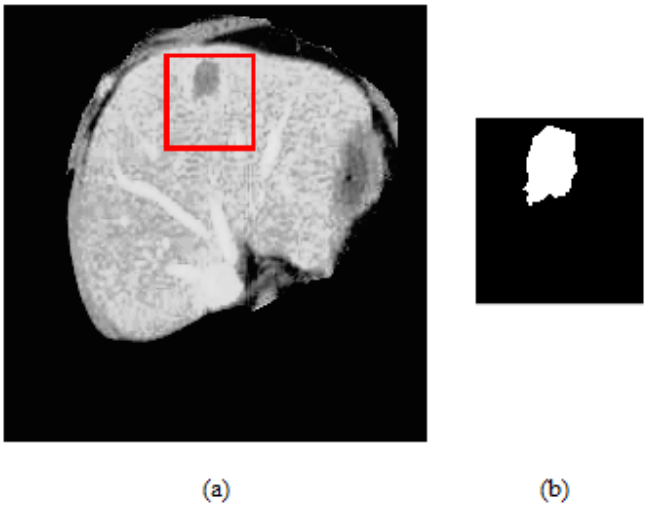


Fig.5 Tumor segmentation applied on enhanced images. (a) ROI (b) Segmented Output

V1. CONCLUSION

This project proposes an optimization-based guided contrast enhancement approach OPTGCE and adaptive gamma correction using DWT-SVD for low contrast CT images. The proposed technique adopts a context-aware 2D histogram-based scheme of exploiting information in the better perceptual quality guidance image for global contrast enhancement, while local image structures are enhanced through SSIM based measure in an optimization framework. This combination effectively improves the contrast while minimizing the artifacts associated with typical histogram-based enhancement methods to preserve the morphological information of the image during enhancement. The qualitative and quantitative analysis using metrics including entropy, MCCEE, and MIGLCM shows the superiority of the proposed method in comparison with the existing methods that do not include guidance mechanism. Finally, a tumor segmentation algorithm is applied on the enhanced images to analyze the performance of the proposed method in facilitating tumor segmentation.

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