

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

1. 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.

2. RELATED WORK

Several image enhancement methods have been proposed in the literature including spatial domain [2, 4, 6] and transform domain methods [1, 11]. 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 decomposition offers the possibility to denoise the signal and enhance contrast [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 or-

der 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. Nevertheless, the method fails for low light images. Jiang et. al. used dark channel prior model to improve perceptual quality of videos [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. 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. 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 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], 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 [8, 18]. The authors used 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, 13, 14]. Two dimensional histogram gives the count of pairwise occurrence of every pixel pair existing in the image. One such approach uses 1D CDF to map input 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 [12, 13, 14]. The motivation behind proposed scheme is to exploit contextual information. The idea of 2D histogram processing has also been applied to video contrast enhancement [13].

Another variant of HE called CLAHE has also been applied to enhance 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. These artificially enhanced images are sometimes pleasant for visual perception, 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 tumors and vessels visible; the vessel and tumor segmentation algorithms work better on enhanced 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].

3. PROPOSED METHOD

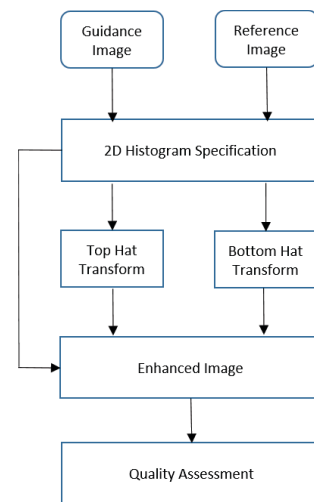


Fig. 1. Proposed Method

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 is to exploit the diversity and the complementary information conveyed by 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. 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 of liver. 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. 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, 35, 36].

3.1. 2D Histogram Specification

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

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

where

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

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

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

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].

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

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

The pixel value mapping is expressed as:

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

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.

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

3.2. Morphological Transforms

Morphological approaches generally exploit structural characteristics of the objects in image [26]. These methods work by sliding a Structuring Element (SE) over the image. Disk shape SE is preferred for medical images because of their rotation invariance characteristics. Disk shaped SE of size 9×9 has been used in this work. Morphological opening eliminates negligible details from the image. Subtracting opening of image from the image itself eradicates the background of image as is done in top hat transform. The top hat transform highlights the objects in image that are smaller than the mask. Similarly, bottom hat transform leaves darker objects in the image [8]. 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.

3.3. 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. Since it is global enhancement technique and the histogram of resultant

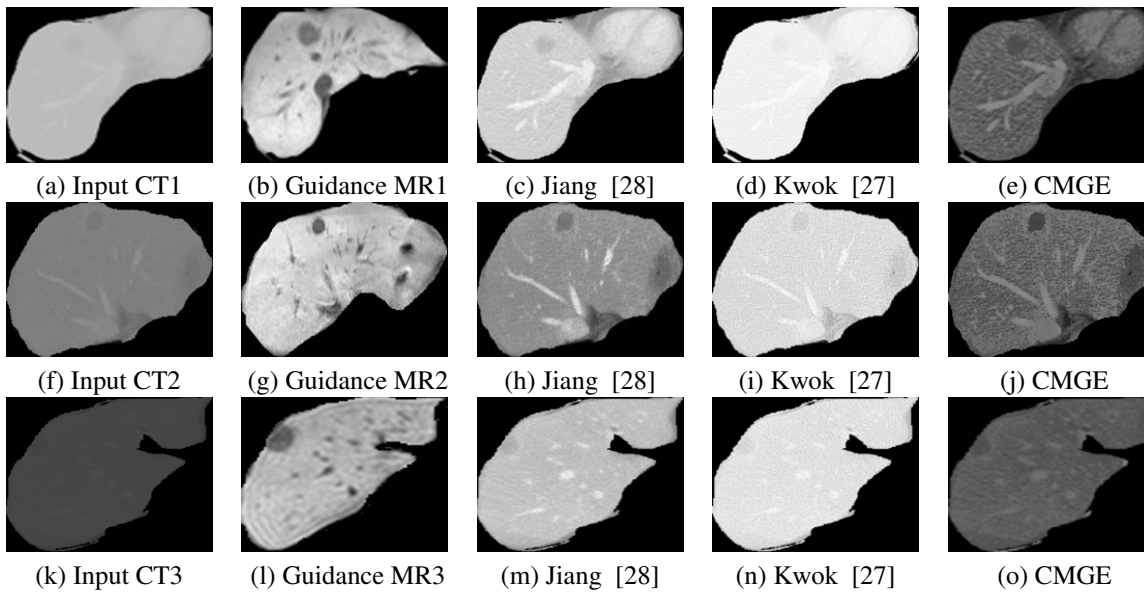


Fig. 2. Visual comparison of our method against state of the art methods

image deviates largely from target histogram, we need to either optimize the enhancement process or apply another enhancement mechanism. Morphological operations are simple but offer strong potential in introducing contrast in medical images. One optimization based enhancement method use Retinex model with l_2 norm [37]. Our work is the first to apply 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 enhancement process.

4. EXPERIMENTS

In this section, we present the dataset used in the experiment and the results obtained. The performance of the proposed method is evaluated in terms of index of quality improvement using contrast evaluation measures, EME and IEM [19, 20, 35]. The obtained results are summarized in tables 1 and 2.

4.1. 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, registration 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.

4.2. 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 [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.

5. 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 manner is to use quantitative measures. A few CEE metrics, as compared to classical image quality assessment context, have been proposed. According to the study in [34, 35, 36], some simple CEE measures have been proven consistent with human judgment of perceptual contrast quality. Here, the enhanced images have been evaluated using quality assessment measures EME [20] and IEM [19]. Both are mathematically expressed here.

$$IEM = \frac{\sum_{m=1}^{k_1} \sum_{l=1}^{k_2} \sum_{n=1}^8 |I_{e,c}^{l,m} - I_{e,n}^{l,m}|}{\sum_{m=1}^{k_1} \sum_{l=1}^{k_2} \sum_{n=1}^8 |I_{r,c}^{l,m} - I_{r,n}^{l,m}|} \quad (8)$$

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:

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

$I_{max}^{l,m}$ and $I_{min}^{l,m}$ refer to maximum and minimum intensity values in the enhanced image. The quantitative results are given in table 1 for the three images separately; table 2 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 1.

Table 1. 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 2. 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

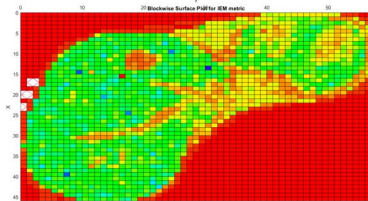


Fig. 3. Surface Plot

6. 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. 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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