PLIP BASED UNSHARP MASKING FOR MEDICAL IMAGE ENHANCEMENT

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ABSTRACT

Medical image enhancement is an effective tool to improve visual quality of digital medical images. In this paper, we propose a new unsharp masking scheme for medical image enhancement. It embeds the PLIP multiplication into the unsharp masking framework. Experimental results demonstrate that the proposed method can effectively enhance the overall contrast and edges of medical images while suppressing background noise.

Index Terms— medical image enhancement, unsharp masking, parameterized logarithmic framework

1. INTRODUCTION

Medical images play an important role in disease detection and diagnosis. They are based on different technologies such as magnetic resonance imaging (MRI), ultrasound imaging, Computerized Tomography (CT), and X-ray imaging. Medical images contain a direct and clear view of the pathological areas. They greatly assist doctors in detecting and diagnosing various diseases. Due to limitations of hardware systems, it is common that medical images present low resolution or low contrast. This, however, makes it difficult to detect diseases in the early stages [1]. Thus, enhancement of digital medical images is necessary and has been one of key research areas of digital image processing.

There are many image enhancement technologies. Histogram equalization (HE) is the simplest and commonly used methods for image contrast enhancement. It attempts to obtain uniformly distributed intensity levels in order to enhance image contrast. However, over-enhancement and emphasis of background noise are common problems of HE. Contrast Limited Adaptive Histogram Equalization (CLAHE) [2] was designed to solve the problems of HE, but it has difficulty to preserve image brightness and brings additional artifacts to enhanced images.

Unsharp masking (UM) is another simple and effective method for image enhancement. It extracts the high frequency part of an image using high-pass filtering and adds it back to the image to enhance the edges and details of the image. But the use of high-pass filtering also poses problems and makes UM extremely sensitive to noises. In addition to this, it also leads to over-enhancement of steep edges. Many improvements of UM were proposed to overcome these disadvantages. Examples include replacing the high-pass filter with an adaptive filter [3] or a quadratic filter [4] or using region segmentation techniques [5]. Recently, Wu et al. [6] developed an improved UM by combining region segmentation with an improved high-pass filter. Siddharth et al. further improved Wu et al.'s method using modified filtering templates [7]. These methods have improved the enhancement performance of UM but there still remain problems such as overshooting artifacts and undesired enhancement performance in the regions with flat contrast.

In order to design an effective method for enhancing medical images, we look into the logarithmic image processing (LIP) [8] model. It is a nonlinear arithmetic framework and was designed to solve the common problems of image processing methods with linear arithmetic operations. LIP has been successfully used for many applications such as image enhancement [9] and edge detection [10]. The parameterized logarithmic image processing (PLIP) framework further improves the LIP model by adding a set of parameters. By replacing linear operations in many image enhancement algorithms with PLIP operations, image quality can be significantly improved [11].

In this work, we propose a new UM scheme for medical image enhancement. It combines the idea of unsharp masking and the PLIP multiplication. The proposed method is capable of enhancing image contrast and details as well as suppressing background noise.

The rest of the paper is organized as follows: section 2 briefly discusses the PLIP multiplication. The proposed UM scheme is introduced in section 3. Section 4 presents the experimental results. The concluding remarks are given in section 5.

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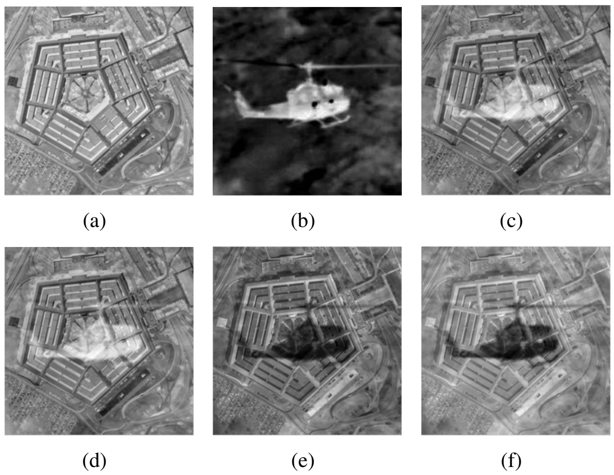


Fig. 1: Image fusion using the PLIP multiplication. (a) gray-tone image of rock image; (b) gray-tone image of copter image; (c) PLIP image multiplication $\mu = 300$, $\lambda = -500$, $\beta = 5$; (d) PLIP image multiplication $\mu = 300$, $\lambda = -1000$ $\beta = 5$; (e) PLIP image multiplication $\mu = 300$, $\lambda = 500$, $\beta = 5$; (f) PLIP image multiplication $\mu = 400$, $\lambda = 1000$, $\beta = 5$.

2. PLIP MULTIPLICATION

Replacing the linear operations with nonlinear operations , the PLIP model better represents the nonlinearity characteristic of images, and offers users more flexibility to choose deferent parameters in order to achieve better performance in image processing. The gray-tone function and multiplication of the PLIP operations are shown as follows: [11]

$$g(i,j) = \mu - f(i,j) \tag{1}$$

$$g_1 \widetilde{*} g_2 = \widetilde{\varphi}^{-1}(\varphi(g_1) \cdot \widetilde{\varphi}(g_2)) \tag{2}$$

$$\widetilde{\varphi}(g) = -\lambda ln^{\beta}(1 - \frac{g}{\lambda}) \tag{3}$$

$$\widetilde{\varphi}^{-1} = \lambda[1 - exp(\frac{-g}{\lambda})^{\frac{1}{\beta}}] \tag{4}$$

where $f(i,j)$ is the original image, $g(i,j)$, g_1, g_2 are the gray-tone functions; μ, λ, β are the PLIP parameters; $\widetilde{*}$ represents the PLIP multiplication.

The choice of parameter μ could be image dependent. For example, it could be set to the maximum value of the image intensity, e.g. $\mu = 256$ for grayscale images. It could also be any other positive value, such as $\mu = 500$. The parameter λ could also be selected as any positive values. Adjusting exponential coefficient β in the PLIP multiplication, users are able to nonlinearly emphasize the brightness of different image regions [11].

Due to the nonlinear properties of the PLIP model, the PLIP multiplication can be used for image fusion. Fig. 1 provides an illustrative example of image fusion using the PLIP multiplication. As can be seen, when given two gray-tone images as inputs, by selecting deferent parameters μ and λ, the PLIP multiplication not only obtains the image fusion results in a gray-tone format but also directly produce the fusion results as the normal gray-scale images. Similarly, if input images are normal gray-scale images, the PLIP multiplication can also directly yield the fusion results in both the gray-tone and grays-cale formats using appropriate parameters.

3. PROPOSED METHOD

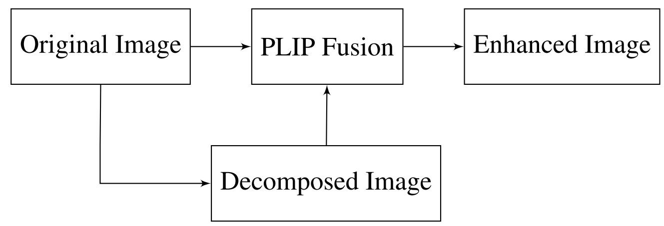


Fig. 2: Block diagram of the proposed scheme

Integrating the PLIP multiplication, this section proposes a new unsharp masking scheme for medical image enhancement. Its block diagram is shown in Fig. 2. The proposed scheme consists of a simple image decomposition to obtain a sub-image and an image fusion process utilizing the PLIP multiplication.

The image decomposition is to extract a sub-image that contains regions of our interest while removing background noise. The decomposition method can be selected base on the property of the image or specific needs. In this paper, we use a threshold method expressed by:

$$L(m,n) = \begin{cases} F(m,n) & F(m,n) \geq t \\ 0 & otherwise \end{cases} \tag{5}$$

where $L(m,n)$ is the extracted sub-image, $F(m,n)$ is the original image, t is the threshold.

After decomposition, the sub-image and the original image are used to perform image fusion using the PLIP multiplication. Firstly, these two images are transformed into gray-tone images G_F and G_L using the gray-tone function in equation (1):

$$G_F(m,n) = \mu - F(m,n) \tag{6}$$

$$G_L(m,n) = \mu - L(m,n) \tag{7}$$

The PLIP multiplication is then applied to G_F and G_L as follows:

$$M(m,n) = G_F \widetilde{*} G_L = \widetilde{\varphi}^{-1}(\widetilde{\varphi}(G_F) \cdot \widetilde{\varphi}(G_L)) \tag{8}$$

where

$$\widetilde{\varphi}(G) = -\lambda ln^{\beta}(1 - \frac{G}{\lambda}) \tag{9}$$

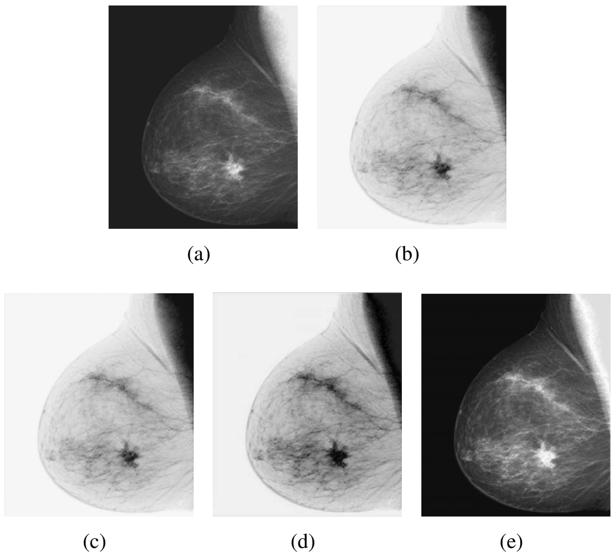


Fig. 3: An illustrative example of the proposed UM scheme. (a) The original image, (b) gray-tone image of original image, (c) gray-tone image of sub-image, (d) PLIP multiplication result and (e) enhanced image.

$$\widetilde{\varphi}^{-1}(G) = \lambda[1 - exp(\frac{-G}{\lambda})^{\frac{1}{\beta}}] \tag{10}$$

The enhanced image $E(m, n)$ is obtained by applying the same gray-tone function on the result of the PLIP multiplication $M(m, n)$:

$$E(m, n) = \mu - M(m, n) \tag{11}$$

Fig. 3 shows the results of each step in the proposed UM scheme. As can be seen, the original image and sub-image are transformed into their negatives, after the fusion with PLIP multiplication, the enhanced image is transformed back into a normal image.

4. EXPERIMENT RESULTS

4.1. Parameter selection

Selecting deferent thresholds t will result in deferent regions being enhanced. Using deferent parameters μ and λ allows users to obtain the optimal result of the enhanced image.

As shown in Fig. 4 (b) and (c), if we choose a larger threshold, less regions in the original image are enhanced. Choosing larger values of μ and λ is able to adjust the sensitivity of the PLIP multiplication. The parameters are selected in terms of the optimal visual effect or the maximum result of quantitative measures.

4.2. Performance comparison

The proposed UM scheme has been applied to many medical images. Several enhanced results are presented here.

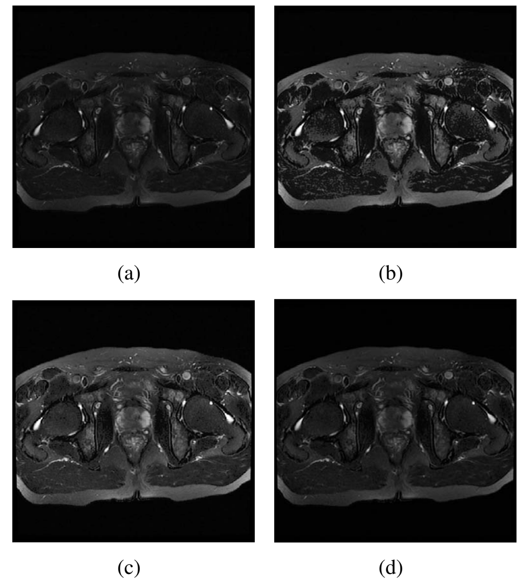


Fig. 4: Image enhancement using different parameter settings. (a) The original image; (b) enhanced image with $t = 25$, $\mu = 200$, $\lambda = -400$, $\beta = 2$; (c) enhanced image with $t = 15$, $\mu = 200$, $\lambda = -400$, $\beta = 2$; (d) enhanced image with $t = 15$, $\mu = 500$, $\lambda = -1000$, $\beta = 2$.

The proposed UM scheme is compared with most commonly used contrast enhancement methods including the histogram equalization (HE), contrast-limited adaptive histogram equalization (CLAHE), conventional unsharp masking (UM), and improved UM algorithm proposed by Siddharth et al.[7].

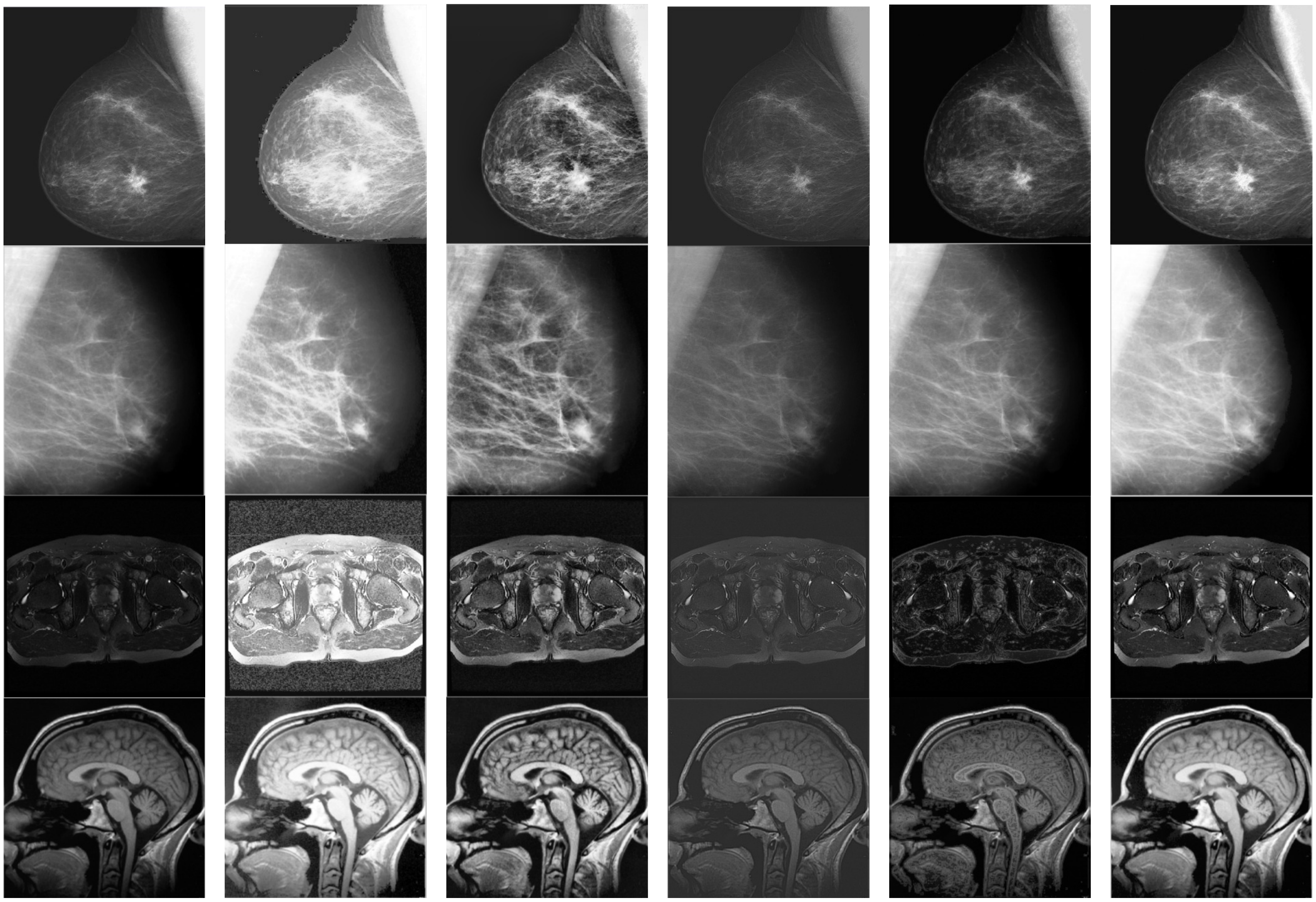
The comparison of enhancement results are presented in Fig. 5. The draw back of HE is obvious because the brightness regions in images are overshoot as shown in Fig. 5(b). CLAHE enhances the overall contrast of images. However, it also enhances noise and brings artifacts to the enhanced images.

As shown in Fig. 5 (d), linear UM is sensitive to noise. Using factors 3 and 5 and filtering template T_1 [7] the improved UM [6] has an improved enhancement performance in mammogram images where edges and details are greatly enhanced. However, it performs poorly in low contrast regions in the CT scan images.

The proposed method, as shown in Fig. 5 (f), is able to provide visually pleasant enhanced images with enhanced contrast and details and shows better performance than other methods in enhancing both mammogram and CT scan images.

4.3. Objective evaluation

The assessment of enhancement results remains a challenging problem because it is often subjective. It is necessary to apply an objective criteria in order to quantitatively evaluate the



(a) (b) (c) (d) (e) (f)

Fig. 5: Image enhancement using different methods. (a) Original image, (b) HE, (c) CLAHE, (d) linear unsharp masking, (e) improved unsharp masking and (f) the proposed method.

enhancement results and to help users obtain the most favorable enhanced images. Because EMEE has been proven to be effective in evaluating image enhancement [12], it is adopted as the objective evaluation measure in this paper.

The EMEE measure result is obtained by dividing an input image $I(i,j)$ into sub-images of size $k_1 \times k_2$, calculating the maximum ($I_{max,k,l}$ and minimum ($I_{min,k,l}$) values of each sub-image and applying those values in equation (12) [13]:

$$EMEE_{\alpha,k_1,k_2} = \frac{1}{k_1k_2}\sum_{l=1}^{k_1}\sum_{k=1}^{k_2}\left[\alpha\left(\frac{I_{max,k,l}}{I_{min,k,l}}\right)^{\alpha} ln\left(\frac{I_{max,k,l}}{I_{min,k,l}}\right)\right] \tag{12}$$

where α is a constant. A higher EMEE value suggests better image enhancement. In this paper α is set to 1, and the sub-image size is set to 4×4.

Table 1 shows the EMEE values of the enhancement results of several testing images by different enhancement methods. As can be seen, the proposed method has a better enhancement performance than other methods.

Table 1: EMEE evaluation

Image	HE	CLAHE	Linear UM	Improved UM	Proposed Method
Mammogram 1	0.08	0.293	0.061	0.272	**0.334**
Mammogram 2	0.161	0.222	0.139	0.130	**0.752**
Scan 1	0.953	2.294	0.187	0.252	**2.661**
Scan 2	1.658	2.913	0.252	2.285	**4.324**

5. CONCLUSION

Conventional HE and UM methods suffer from problems such as over-enhancement and noise sensitivity. In this paper, we have proposed a new enhancement method for medical images combining the unsharp masking scheme with the PLIP multiplication. The experimental results have demonstrated that the proposed method is able to enhance details and edges in medical images while suppressing background noise. Objective evaluation measure have also confirmed that the proposed method has better performance than several existing enhancement methods.

6. REFERENCES

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