Comparative Study of Logarithmic Image Processing Models for Medical Image Enhancement

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Abstract—Medical image enhancement is an effective tool to improve visual quality of digital medical images. However, conventional linear image enhancement methods often suffers from problems such as over-enhancement and noise sensitivity. In this paper, we study nonlinear arithmetic frameworks designed to solve the common problems of linear enhancement methods, namely, LIP, PLIP and GLIP. We also introduce nonlinear unsharp masking algorithms based on the logarithmic image processing models for medical image enhancement. Experiments are conducted to evaluate and compare the performance of the methods.

Index Terms—medical image enhancement, unsharp masking, logarithmic image processing, parameterized logarithmic image processing, generalized logarithmic image processing

I. INTRODUCTION

Medical images play a crucial part in today's medical diagnosis. Medical imaging technologies such as Computerized Tomography (CT), magnetic resonance imaging (MRI) and X-ray imaging provide clear and direct view of the pathological areas. They are essential tools for detecting and diagnosing various diseases. However, due to the limitation of imaging hardware, obtained medical images often present low resolution or low contrast. Medical image enhancement aims to improve medical image contrast or emphasis certain features. It is necessary to increase the detection rate of various disease and it has been one of the key research areas of digital image processing.

There are many image enhancement technologies. Histogram equalization (HE) is one of the simplest and most commonly used method for image contrast enhancement. It computes the probability density function of the image, and map each intensity value to a new value so that the image intensity is more uniformly distributed [1]. However, it suffers from problems such as over-enhancement and emphasis of background noises. Many histogram based algorithms are developed over the years, such as Contrast Limited Adaptive Histogram Equalization (CLAHE) [2], brightness preserving bi-histogram equalization (BBHE) [3]. They have improved performance, but cannot eliminate the problems.

Unsharp masking (UM) is another interesting approach for image enhancement. The high frequency details of a input image are extracted using a hight-pass filter, amplified and added back to the image. It aims to enhance the edges and details, but the use of a high-pass filter also makes the method extremely sensitive to noise. In addition to this, steep edges are often over-enhanced when a global gain is used to amplify the detail information. Different methods are proposed to improve the performance of UM. Examples include replacing the high-pass filter with an adaptive filter [4] or a quadratic filter [5] or using region segmentation techniques [6]. However, problems like overshooting and artifacts persists.

The logarithmic image processing (LIP) model is a nonlinear arithmetic framework designed to solve common problems of linear image processing methods. Under the LIP model, light intensity is modeled logarithmically, and a set of arithmetic operations are provided to replace linear operations [7]. The LIP model has been adopted for various applications such as image enhancement [8] and edge detection [9]. The Parameterized LIP (PLIP) model further improves the LIP model by adding a series of parameters, by changing the parameters, the PLIP provides more flexibility in terms of enhancement effect [10]. The generalized LIP (GLIP) model combines the gigavision sensor model with the LIP model. It provides new image representation and operations [11]. It is also effective in handling common image processing problems.

In this paper, we study the definitions and properties of LIP, PLIP and GLIP. In order to study and compare the performance of the logarithmic image processing models for medical image enhancement, we also introduce new nonlinear unshrp masking algorithms that combine a generalized unsharp masking framework [12] with logarithmic image processing models. The proposed algorithms are designed to enhance both contrast and edges of medical images. Experiments are also conducted to compare and evaluate their performances.

The rest of the paper is organised as follows: in section II we discuss the logarithmic image processing models. Section III introduces new non unsharp masking methods. Section IV presents the experiment results. A few concluding remarks are given in section V.

II. LOGARITHMIC IMAGE PROCESSING MODELS

In this section we will review the conventional LIP model, the PLIP model and the GLIP model. The definition and properties of each model is discussed.

A. LIP

In conventional LIP model, the light intensity of a grayscale image is represented by the amount of light passing through a light absorbtion filter [7]. The addition of two images can be considered as putting two filters together. The light absorbtion filter can be expressed by the gray-tone function:

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

where $f(i,j)$ is the original image, $g(i,j)$ is output in gray-tone format, M represents the greatest intensity value of the image.

Through the isomorphic function:

$$\varphi(g) = -Mln(1 - \frac{g}{M}) \tag{2}$$

$$\varphi^{-1} = M[1 - exp(\frac{-g}{M})] \tag{3}$$

nonlinear LIP operations can be constructed corresponding to common linear operations such as addition, subtraction and scalar multiplication:

$$g_1 \oplus g_2 = \varphi^{-1}[\varphi(g_1) + \varphi(g_2)] \tag{4}$$

$$g_1 \ominus g_2 = \varphi^{-1}[\varphi(g_1) - \varphi(g_2)] \tag{5}$$

$$c \otimes g = \varphi^{-1}[c\varphi(g)] \tag{6}$$

where $\oplus$, $\ominus$ and $\otimes$ denote addition, subtraction and scalar multiplication under LIP model respectively. The equations can be further derived into the following expressions[7] [10]:

$$g_1 \oplus g_2 = g_1 + g_2 - \frac{g_1 g_2}{M} \tag{7}$$

$$g_1 \ominus g_2 = M\frac{g_1 - g_2}{M - g_2} \tag{8}$$

$$c \otimes g = M - M(1 - \frac{g}{M})^c \tag{9}$$

LIP models more properly represents the nonlinearity characteristics of images. By replacing linear operations with nonlinear LIP operations, the performance of linear image enactment algorithms can be improved.

B. Parameterized LIP

The PLIP model improves LIP model by introducing a series of parameters. Same as the LIP, under PLIP model an input image is firstly transformed into a gray-tone image, then nonlinear PLIP operations are used instead of linear operations. The operations can be expressed as [10]:

$$g(i,j) = \mu - f(i,j) \tag{10}$$

$$g_1 \widetilde{\oplus} g_2 = g_1 + g_2 - \frac{g_1 g_2}{\gamma} \tag{11}$$

$$g_1 \widetilde{\ominus} g_2 = k\frac{g_1 - g_2}{k - g_2} \tag{12}$$

$$c\widetilde{\otimes}g_1 = \gamma - \gamma(1 - \frac{g}{\gamma})^c \tag{13}$$

where $g(i,j)$ is the gray-tone function, $\widetilde{\oplus}$, $\widetilde{\ominus}$ and $\widetilde{\otimes}$ denotes PLIP addition, subtraction and scalar multiplication respectively. μ, k and γ are PLIP parameters.

Unlike LIP model, in which M is a fixed constant, parameter μ can be chosen flexibly. It can be the maximum intensity value of the image, for example, $\mu = 255$, or any other positive values such as $\mu = 500$. Similarly, k and γ can also be chosen as any positive value.

The PLIP offers more flexibility than the conventional LIP model. By using different parameters the user can control the outcome of the enhancement algorithms based on the properties on images or specific applications.

C. Generalized LIP

The gigavision sensor (GVS) is an imaging device that responds to light logarithmically [13]. It can be described by a statistical model. The GLIP model combines the idea of the GVS with the LIP. In the GVS model the expected pixel value can be mapped into expected energy using the following equation [11]:

$$\Phi_T(v) = -M\left[a_T ln(1 - (\frac{v}{M})^{\frac{1}{T}}) + b_T\right] \tag{14}$$

where v and T represent the expected pixel value and threshold of GVS model, a_T and b_T are constants. When $a_1 = 1$, $b_1 = 0$, $T = 1$, the function is equivalent to the isomorphic function of LIP. Thus, LIP can be considered as a special case of GLIP.

Given the previous function the operations of the GLIP model can be expressed as:

$$v_1 \boxplus v_2 = M\left[1 - \Gamma\left(T, \frac{\Phi_T(v_1) + \Phi_T(v_2)}{M}\right)/\Gamma(T)\right] \tag{15}$$

$$c \boxtimes v = M\left[1 - \Gamma\left(T, \frac{c\Phi_T(v)}{M}\right)\right] \tag{16}$$

where $\boxplus$ and $\boxtimes$ represents the GLIP addition and scalar multiplication. $\Gamma(x)$ and $\Gamma(a,x)$ are the gamma function and incomplete gama function.

III. LIP, PLIP AND GLIP BASED UNSHARP MASKING

In this section we introduce an unsharp masking framework for medical image enhancement. It combines a generalized unsharp masking algorithm [12] with operations of LIP, PLIP and GLIP. Its block diagram is depicted in Fig 1. An IMF filter is firstly applied on the input image to generate a smoothed image s. A detail image d is then generated and amplified. The contrast of the smoothed image s is enhanced using adaptive histogram equalization procedure, the result is fused with the amplified detail information to produce the final enhanced output. By using operations of LIP, PLIP and GLIP modles, we can developed three algorithms with distinctive effect.

The IMF filtering can be expressed as $s_{k+1} = M(s_k)$, where $M(s)$ represents the median filter operation, and $k = (0, 1, 2...)$ is the iteration index. The detail image is produced by taking the LIP, PLIP or GLIP subtraction of the input
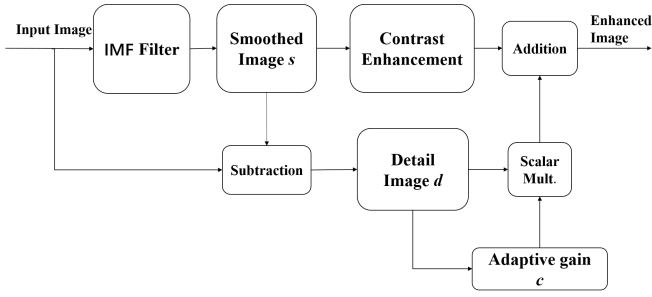
Fig. 1: Block diagram of the proposed algorithm.

image I and the smoothed image s. Under LIP model this is expressed as [12]:

$$d = I \ominus s \qquad (17)$$

Similarly, for PLIP and GLIP we have $d = I\widetilde{\ominus}s$ and $d = I\boxminus s$ respectively.

To compute the gain used to amplify the detail signal, we firstly map the detail image d to a new image a where

$$a = 2d - 1 \qquad (18)$$

the gain c is then computed using the following equation[12]

$$c(a) = \alpha + \beta exp(-|a|^{\eta}) \qquad (19)$$

parameters α and β are obtained using the following:

$$\beta = (c_{max} - c_{min})/(1 - e^{-1}) \qquad (20)$$

and

$$\alpha = c_{max} - \beta \qquad (21)$$

where c_{max} and c_{min} are the maximum and minimum gain value we specify. Using LIP, PLIP and GLIP scalar multiplication the detail information is amplified. The operations can be expressed as: $c \otimes d$, $c\widetilde{\otimes}d$ and $c \boxtimes d$.

The contrast of s is enhanced using adaptive histogram equalization, in this paper it is implemented using Matlab function "adapthisteq" [12]. The result f is fused with the detail image to form the enhanced image E, which can be expressed as: $E = f \oplus (c \otimes d)$, $E = f\widetilde{\oplus}(c\widetilde{\otimes}d)$ and $E = f \boxplus (c \boxtimes d)$ for LIP, PLIP and GLIP models.

IV. EXPERIMENT RESULTS

A. Parameter selection

By changing the parameters, we can adjust the enhancement result of the proposed unsharp masking scheme. Changing c_{max} and c_{min} affect how much the detail information is amplified. Setting deferent PLIP parameters μ, κ and γ changes the sensitivity of the PLIP based algorithm. Choosing deferent threshold T for the GLIP model also changes the sensitivity of the algorithm. An example is illustrated in Fig. 2.

As shown in Fig. 2, given larger c_{max}, the detail image will have larger contribution to the final result. By setting larger PLIP parameters, the sensitivity of the algorithm is modified. Changing T of GLIP model has a similar effect. The parameters are selected in terms of the optimal visual effect or the maximum result of quantitative measures.
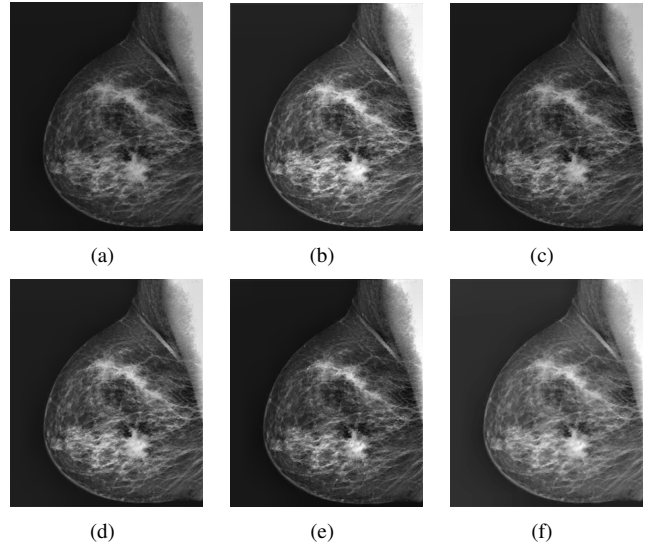

(a) (b) (c)

(d) (e) (f)

Fig. 2: Enhancement result using different parameter settings. (a) LIP model $c_{max} = 5$, $c_{min} = 1$; (b) LIP model $c_{max} = 3$, $c_{min} = 1$; (c) PLIP model $c_{max} = 5$, $c_{min} = 1$, $\mu = \kappa = \gamma = 300$; (d) PLIP model $c_{max} = 5$, $c_{min} = 1$, $\mu = \kappa = \gamma = 500$; (e) GLIP model $c_{max} = 5$, $c_{min} = 1$, $T = 3$; (e) GLIP model $c_{max} = 5$, $c_{min} = 1$, $T = 7$.

B. Performance comparison

In this section we compare the proposed nonlinear unsharp masking methods using LIP, PLIP and GLIP models with some conventional image enhancement methods, namely, histogram equalization (HE) and linear unsharp masking (UM).

As we can see in Fig. 3. The image processed by HE is over-enhanced as shown in Fig. 3 (b). Both HE and linear UM are very sensitive to noise, adding many artifacts and distortions to the original image.

Methods using LIP, PLIP and GLIP have significantly better performance than conventional linear methods. The proposed LIP-UM can effectively enhance image contrast and detail while suppressing over-enhancement. By setting suitable parameters, PLIP UM can provide even more desirable enhancement result. GLIP-UM and PLIP-UM has similar overall effect. In terms of details, GLIP-UM is more effective at enhancing edges and small details, but it is also more sensitive to noise than PLIP-UM and LIP-UM.

C. Objective evaluation

To objectively evaluate the performance of the algorithms, we adopt the quantities measure SDME to access the experimental result in this paper.

The SDME can be defined by the following equation [14]:

$$SDME$$
$$= -\frac{1}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} 20ln \left| \frac{I_{max,k,l} - 2I_{center,k,l} + I_{min,k,l}}{I_{max,k,l} + 2I_{center,k,l} + I_{min,k,l}} \right| \qquad (22)$$

where the image is divided into sub-blocks of size $k_1 \times k_2$, $I_{center,k,l}$ denotes the center value of each block, $I_{max,k,l}$
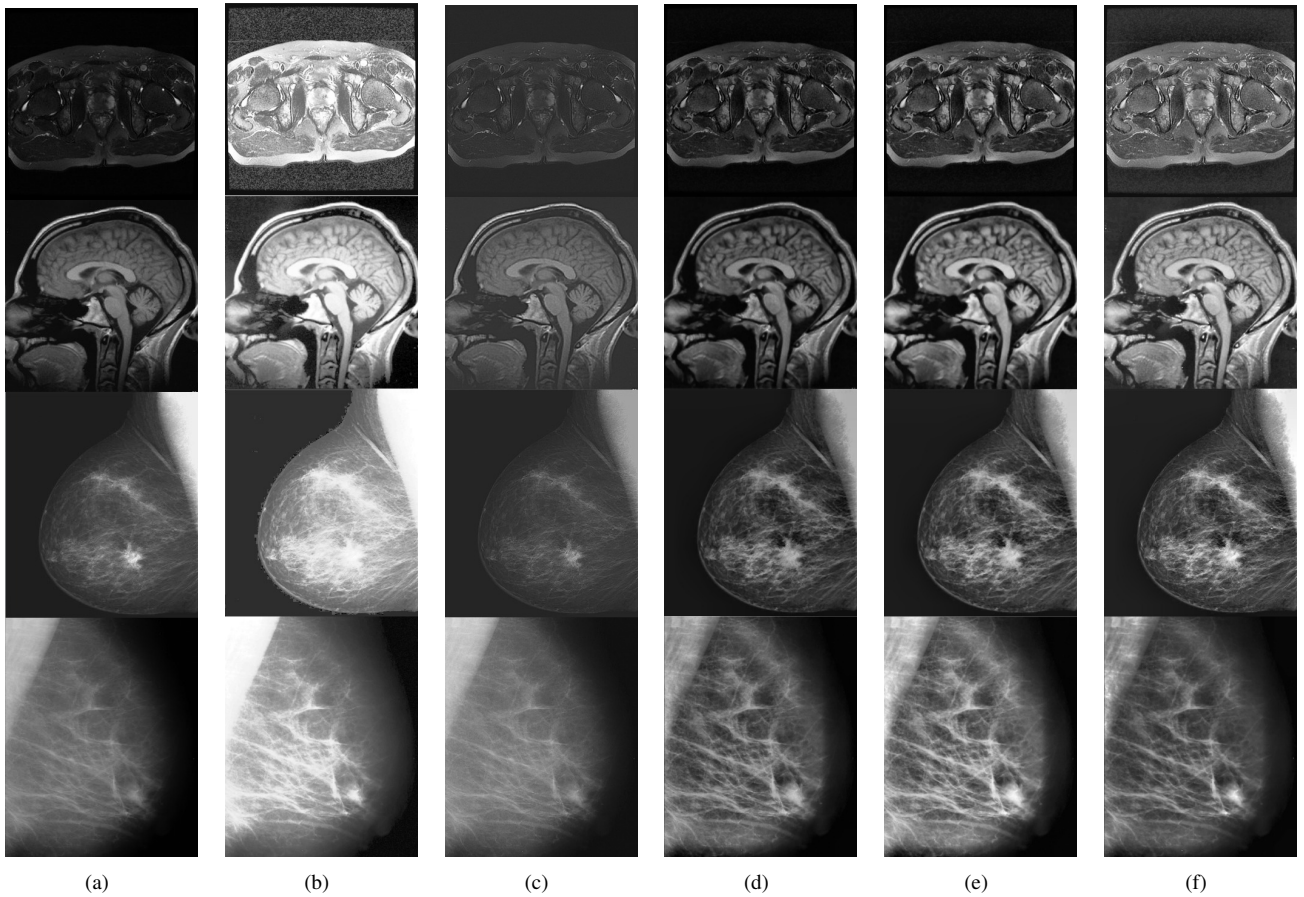
Fig. 3: Image enhancement using different methods. (a) Original image, (b) HE, (c) UM, (d) LIP-UM, (e) PLIP-UM (f) GLIP-UM.

and $I_{min,k,l}$ are the local maximum and minimum value of each block respectively. A higher SDME value indicates better enhancement performance. In this paper, the sub-block size is set to 3×3.

The Table I shows the SDME values of the experimental results. Consistent with what we observed in Fig. 3, methods using nonlinear models have significantly better performance than conventional methods. GLIP-UM and PLIP-UM both have improved performance over LIP-UM, GLIP-UM has some slight advantages on mammogram images, while PLIP-UM is better at processing scan images.

TABLE I: SDME evaluation

Image	scan 1	scan 2	Mammogram 1	Mammogram 2
Original	59.3530	60.7916	85.2240	86.3691
HE	66.3543	64.9267	83.4989	81.1776
UM	48.6278	53.2618	73.8576	73.2956
LIP-UM	68.8334	66.3558	84.1415	90.2288
PLIP-UM	70.5131	68.9957	84.8492	97.4878
GLIP-UM	69.9635	67.1020	86.3819	97.5130

V. CONCLUSION

Using nonlinear arithmetic frameworks is an effective way to solve current problems of linear image enhancement al-gorithms. In this paper we studied the logarithmic image processing models including the LIP, PLIP and GLIP. New unshrp masking using the nonlinear models are introduced for medical image enhancement. Experiment results and objective evaluation proved that methods using logarithmic image processing models have improved performance over conventional methods. They also showed that the GLIP model is better at enhancing edges but the PLIP is less noise sensitive and has the best overall performance.

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