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X-ray image enhancement based on improved Retinex-Net

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***Abstract*—Aiming at the problems of poor visual effect and more noise in practical application of X-ray, as well as the low contrast and difficult to identify the details of X-ray imaging. This paper proposes an X-ray image enhancement algorithm based on the improved Retinex-Net. Firstly, the X-ray image is decomposed into illumination component and reflection component through the decomposition network of Retinex-Net model, and then the illumination component is enhanced through the enhancement network. Secondly, based on the statistical characteristics of the reflection component, the weighted guided filtering and local detail enhancement algorithm are combined to reduce the noise and enhance the detail of the reflection component. Finally, the enhanced illumination component and reflection component are fused and output. By analyzing the results of experiments on X-ray images in different environments and different application scenarios, the algorithm can effectively improve the visual effect and contrast, and suppress the noise while enhancing the detail information.**

Keywords—X-ray image, Image enhancement, Weighted guided filtering, Retinex-Net theory

I. INTRODUCTION

After the discovery of X-ray, it has been widely used in various fields because of its own advantages. In daily life, it is used for contraband detection[1]. In industry, it can be used for device flaw detection and defect detection[2]. In medicine, it is widely used, including digital image photography (DR), computed tomography (CT) and other technologies[3]. Although the use of X-ray photography will decrease with the development of techniques such as nuclear magnetic resonance (MRI), which has particular advantages for the examination of tissues that have cavities inside(such as the lungs). Therefore, it is of great value for its continued research and development. Because of the complicated imaging environment of X-ray images, the produced images have problems such as poor visual effect, more noise and poor contrast. Therefore, enhancement of the X-ray image is required to highlight image useful information, elevating the visual effect of the image. This problems that needs much improvement in the practical application of X-ray images.

At present, conventional methods applied to enhance X-ray images include histogram transform method, gray scale transform, Retinex algorithm, wavelet transform, guide filter and so on. For example, the contrast of X-ray images was enhanced by using sinusoidal grayscale transformation by Yang[4] etc. The Retinex algorithm based on bilateral filtering effectively avoids the halo pseudo-halo phenomenon by Elad[5] etc. Based on irradiation_ Reflection models and bounded operations enhance image texture and detail information by Bi[6] etc. Traditional image enhancement methods need to adjust parameters manually when they are used, which is time-consuming and ineffective. In recent years, with the development of deep neural network, CNN has been widely used in image processing. Inspired by the Retinex model, the Retinex-Net algorithm was proposed by Wei C[7]in 2018. They incorporated the convolution neural network into the Retinex model to achieve auto-tuning. Retinex-Net has a very good effect in improving image visual effect and image contrast, but the theory has a large noise, and its advantage in detail enhancement is not particularly obvious.

Aiming at the shortcomings of X-ray image in practical application, this paper integrates the weighted guided filtering method and local detail enhancement algorithm on the basis of Retinex-Net model. The problem of high noise in Retinex-Net model is improved, and the image details are enhanced, which further improves the practical application of X-ray images.

II. RETINEX-NET MODEL

According to the traditional Retinex algorithm, the image is viewed as the product of the reflection and illumination components:

$$S = R * I \tag{1}$$

As in(1), S represents an image, R represents the reflection component of S[8], and I represents the illumination component of S. The reflection component is the inherent property of the object, which is basically independent of the external lighting conditions. The illumination component is the external light condition, and objects with different exposure degrees have different illumination components. The Retinex-Net model integrates the convolutional neural network into the Retinex model. It changes the estimation of the exposure component in the Retinex model through the Gaussian function into a decomposition network, which can realize the image decomposition through automatic parameter adjustment. The illumination component is then enhanced through an enhancement network. Finally, the enhanced image is obtained by image multiplication. The structure block diagram of Retinex-Net model is shown in Fig.1.

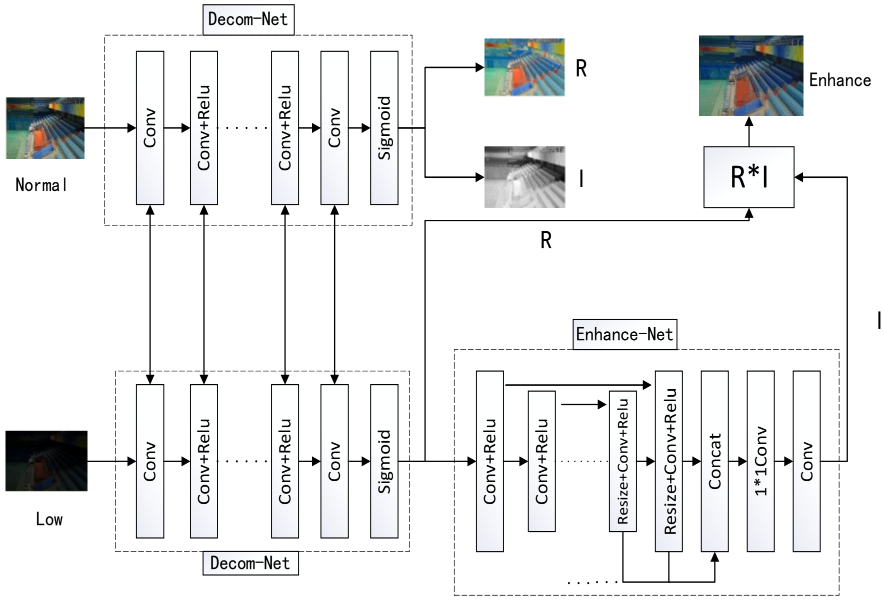


Fig.1. Retinex-Net model structure diagram

III. Improved X-Ray Image Enhancement Algorithm of Retinex-Net

This paper improves the Retinex-Net model. In the Retinex-Net model, noise and detail information exist in the reflection component, so the reflection component in this paper is studied and improved. Firstly, the X-ray image is decomposed into illumination component and reflection component through the decomposition network in the Retinex-Net model, and then the illumination component is enhanced through the enhancement network. In the process of enhancing the reflection component, the reflection component reduce the noise by weighted guided filtering, which can avoid the phenomenon of false halo and remove the noise at the same time. Secondly, the local detail enhancement algorithm is used for enhancement, which greatly enhances the detail information. Finally, the enhanced image is obtained by multiplying the enhanced illumination component and the reflection component. First, the 3*3 convolution layer is used to extract information from the input image. Secondly, the image is mapped to R and I through the five 3*3 convolution layers of the activation function, and a 3*3 convolution layer is used to project R and I from the feature space. Finally, the sigmoid function is used to constrain R and I within the range of [0,1]. As a product of the development of deep learning, Retinex Net adopts data-driven method to adjust parameters and realizes automatic parameter adjustment. Retinex Net can adapt to image decomposition of different quality and participate in batch processing. The structural block diagram of the improved Retinex-Net X-ray image enhancement algorithm is shown in Fig.2.

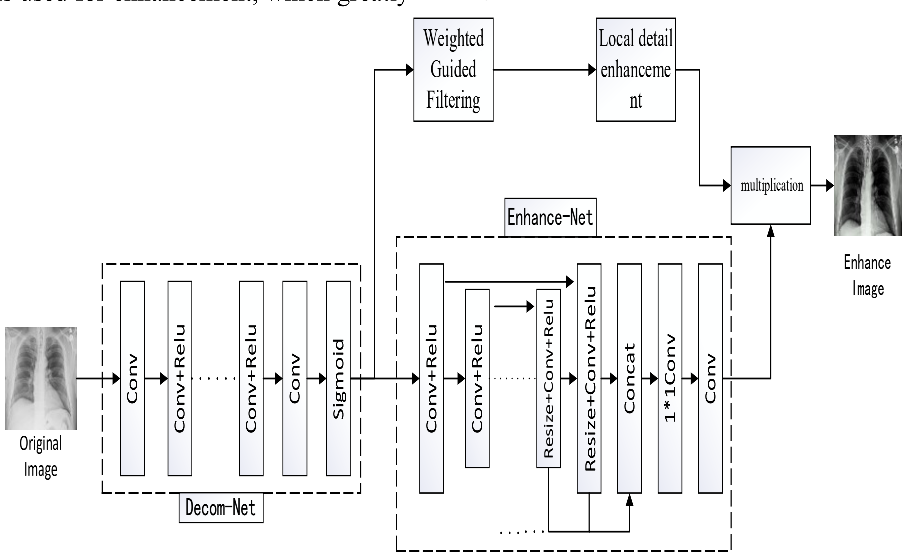


Fig.2. Structure block diagram of the improved Retinex-Net X-ray image enhancement algorithm

A. Weighted Guided Filtering

Guided filter is a new type of local linear filter, which is a linear shift invariant filtering process. Because of the original guided filter algorithm, the same is used in different windows ε Adjustment factor. It does not take into account the differences between the pixels in different windows, making edge preservation less effective.

In this paper, the reflection component of Retinex-Net is enhanced. The purpose of enhancement is to retain the detail information to the greatest extent while removing noise, in order to enhance the details later. The weighted guided filtering is very suitable for the enhancement conditions of this paper. It is an edge-preserving denoising filtering method, which can retain edge detail information while denoising. The improved weighted guided filtering method is very significant for the preservation of detailed information. The weighted guided filtering calculates the edge weight through the local variance in the 3*3 window, and adjusts the coefficient ε from the edge weight to enhance the robustness of the algorithm. The method is shown in(2):

$$\Gamma_{\mathrm{G}}(\mathrm{i}) = \sum_{\mathrm{i}'=1}^{N} \frac{\sigma_{G,1}^2(\mathrm{i}) + \gamma}{\sigma_{G,1}^2(\mathrm{i}') + \gamma} \tag{2}$$

As in(2), G is the guide image; $\sigma_{\mathrm{G},1}^2$ is the variance of G in the 3*3 neighborhood of the central pixel; γ Take $(0.001*L)^2$;L is the gray value range of the image; N is the total number of pixels.

In weighted guided filtering, the pixel edges of corresponding images need to be calculated by variance, but not all images have pixel edges with large variance. In view of the above situation, Wang Zhigang et al[9]. used the edge weight of Canny operator to replace the local variance in the literature, which can reduce the noise while retaining the edge information very well. The improved weight factor is shown as(3):

$$\Gamma_{\mathrm{G}}(\mathrm{i}) = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}'=1}^{\mathrm{N}} \frac{C_B(\mathrm{i}) + \gamma}{C_B(\mathrm{i}') + \gamma} \tag{3}$$

As in(3),$C_B$is Canny operator; γ Take (0.001*L)2;L is the gray value range of the image; N is the total number of pixels.

With the above improvements, the cost function of weighted guided filter used I n this paper is shown as(4):

$$E(a_k, b_k) = \sum_{i \in w_k} \left[(a_k I_i + b_k - p_i)^2 + \frac{\varepsilon}{\Gamma_{\mathrm{G}}(\mathrm{i})} a_k^2 \right] \tag{4}$$

The coefficient (a,b) obtained by linear regression is shown as(5):

$$a_k = \frac{\frac{1}{|\omega|} \sum_{i \in \omega_k} I_i P_i - u_k p_k}{\sigma_k^2 + \frac{\varepsilon}{\Gamma_{\mathrm{G}}(\mathrm{i})}}$$

$$b_k = p_k - a_k u_k \tag{5}$$

As in(5), ε to adjust parameters to prevent a_k is too large; u_k is the average of I within w_k; σ_k^2 is the variance of I in w_k; p_k is the mean value of the input image p within w_k; $|\omega|$ is the number of pixels within the w_k.

B. Local Detail Enhancement Method

The reflection component filtered by weighted guidance contains a large amount of detail information. According to the statistical characteristics of the reflection component, this paper adopts the local detail enhancement algorithm to effectively enhance the detail of the denoised reflection component. The local detail enhancement algorithm adopted in this paper is to multiply the local high-frequency components by the correction parameters to enhance the image detail information. Different correction parameters are selected according to the different high-frequency components. The higher the frequency, the larger the correction parameters are selected. The size of high frequency components is determined by local variance. The size of the correction parameter is determined by the size of the high frequency component

For example, in the local space with side length N, if the pixel$(\mathrm{i,j})$ has gray value $\mathrm{x(i,j)}$, The local average value of pixels is displayed as(6):

$$u(i,j) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \mathrm{x(i,j)} \tag{6}$$

Its local variance can be expressed as(7):

$$\sigma_{(i,j)}^2 = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} [x(i,j) - u(i,j)]^2 \tag{7}$$

The local detail enhancement process is shown as (8):

$$\begin{aligned} f(i,j) &= \left[x(i,j) - u(i,j) \times C_p\right] + u(i,j) \\ C_p &= C_1 \qquad 0 \le \sigma_{(i,j)}^2 \le t_1 \\ C_p &= C_2 \qquad t_1 \le \sigma_{(i,j)}^2 \le t_2 \\ C_p &= C_3 \qquad t_2 < \sigma_{(i,j)}^2 \end{aligned} \tag{8}$$

As in(8), $t_1$and $t_2$is threshold; C_p is a correction parameter $C_1 < C_2 < C_3$ .The output reflection component after this method can be shown in(9):

$$f(i,j) = \mathrm{x(i,j)} + \frac{C}{\sigma(i,j) + s} \cdot [x(i,j) - u(i,j)] \tag{9}$$

As in(9), $\mathrm{x(i,j)}$ is the gray value of a pixel in the image, $f(i,j)$ is the gray value after $\mathrm{x(i,j)}$ enhancement, and $u(i,j)$ is the local mean value, $\sigma(i,j)$ is LSD, C is local contrast control, and S is a small amount greater than zero, which can be ignored.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

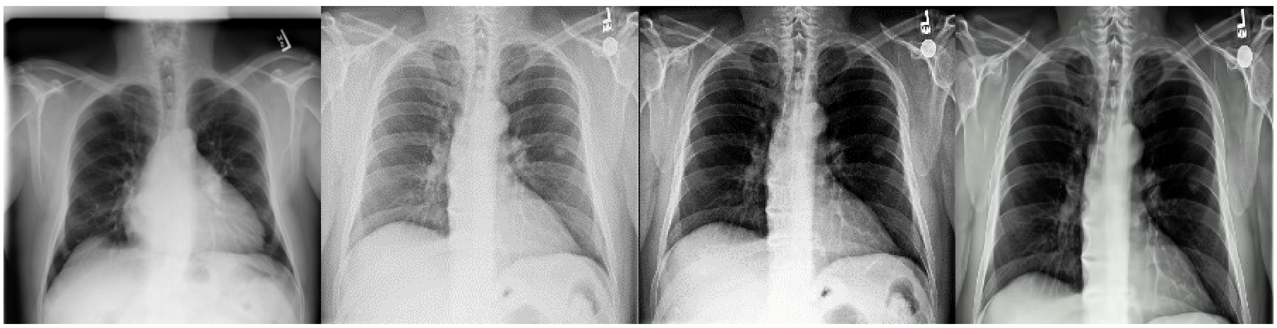
In this paper, X-ray images of different data sets are enhanced, including chestX-ray image data set chestX-ray, bone X-ray image data set MURA and industrial detection X-ray image data set GD X-ray. The algorithm of Retinex and Retinex-Net is compared with the algorithm of this paper, and analyzed from both subjective and objective aspects.

A. Subjective Analysis

Subjectively, the experimental results of X-ray images under different application backgrounds under the algorithm in this paper are compared with the experimental results under the other two algorithms.

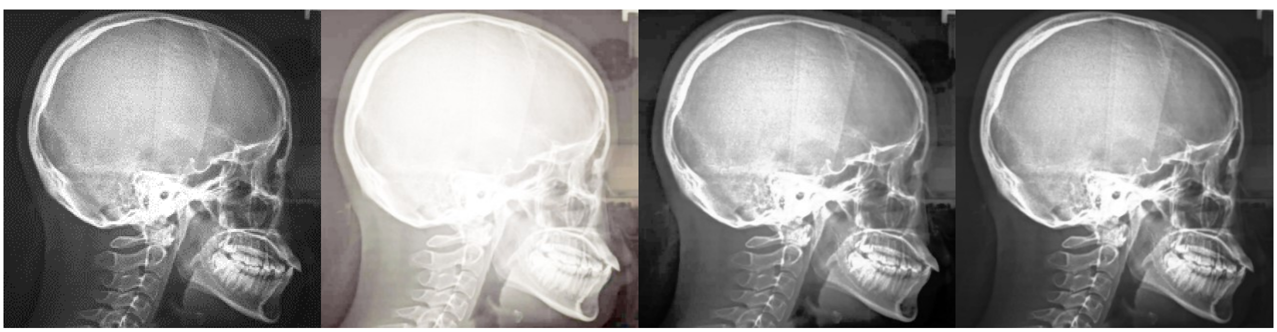
Fig.3, Fig.4, and Fig.5 are illustrations of the enhancement effect of each algorithm on the X-ray image. From the actual effect, The chest and bone X-ray images of Retinex are excessively enhanced, and the images are overexposed, which is not conducive to practical application. Retinex-Net algorithm can enhance the X-ray images in three application environments, but there is a phenomenon of halo and pseudo halo, and it contains more noise. Retinex-Net enhancement does not conform to the practical application of X-ray images. In this algorithm, the enhanced X-ray image effect is very significant, and this excellent effect is particularly evident in Fig.3. It can be seen that the visual effect of the chest X-ray image in Fig.3. has been significantly improved, and the noise has been successfully suppressed, especially for the enhancement of detail information.

It can be seen from the enhancement effect of different algorithms on X-ray images. The algorithm in this paper is very effective for X-ray image enhancement. The algorithm structure of this paper adopts the framework of Retinex-Net model to realize automatic parameter adjustment and batch operation. It provides a convenient and effective method for the efficient practical application of X-ray images in medicine and industry.



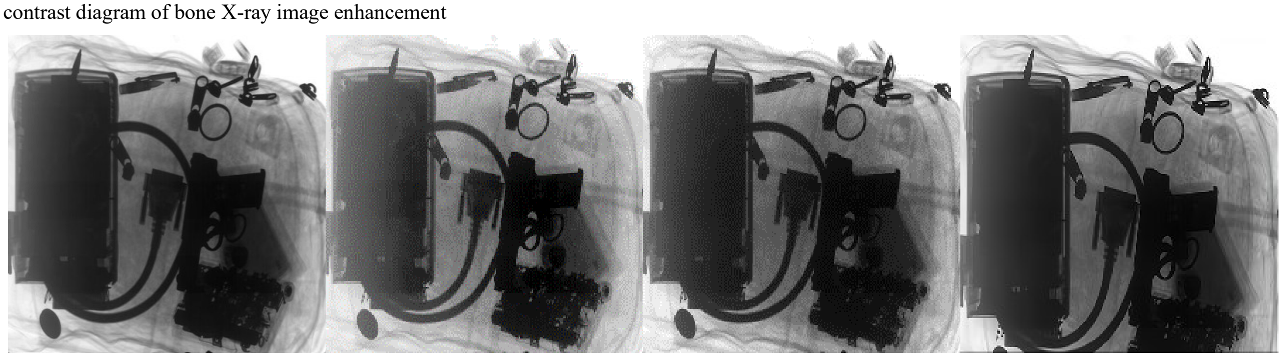
a) Original Fig　　b) Retinex　　c) Retinex-Net　　d) Improve Retinex Net

Fig. 3 contrast enhancement of chest X-ray image



a) Original Fig　　b) Retinex　　c) Retinex-Net　　d) Improve Retinex Net

Fig. 4 contrast diagram of bone X-ray image enhancement



a) Original Fig　　b) Retinex　　c) Retinex-Net　　d) Improve Retinex Net

Fig. 5 contrast diagram of industrial inspection X-ray image enhancement

B. Objective Analysis

Objectively, this paper compares the experimental results of different algorithms from the two aspects of information entropy and average gradient. The image information entropy H is shown in (10):

$$\mathrm{H} = -\sum_{x \in k} q(x) \ln q(x) \tag{10}$$

As in(10), q (x) represents the distribution density at which the image gray level is x; K is the image gray level. The information entropy represents the average information of the image. Large information entropy contains more average information.
The average gradient G is expressed as follows (11):

$$\mathrm{G} = \frac{1}{(M-1)(N-1)} \left\{ \frac{1}{2} \left[(x(i,j) - x(i+1,j))^2 + (x(i,j) - x(i,j+1))^2 \right] \right\}^{\frac{1}{2}} \tag{11}$$

As in (11), M, N are the length and width of the image, respectively. x (i, j) is the gray value of the image at the pixel point (i, j). The average gradient reflects the rate of detail change of the image, and can be used to characterize the clarity of the image. The large average gradient contains rich image details, and the image is very clear.

In order to make the objective analysis clearer, the objective indicators of various algorithms are listed in Table I.

TABLE I OBJECTIVE METRICS FOR DIFFERENT AUGMENTATION ALGORITHMS

Different dataset parameters	ChestX-ray		MURA		GDX-ray	
	H	*G*	*H*	*G*	*H*	*G*
Original Fig	6.97	4.97	7.32	3.65	7.56	1.56
Retinex	7.43	3.68	6.56	2.93	6.32	1.45
Retinex-Net	7.98	6.32	7.32	4.65	7.60	1.68
Improve Retinex Net	8.36	7.68	8.12	5.91	7.98	3.63

Table I objectively reflects that the algorithm in this paper is very effective in improving the overall visual effect and detail effect of the image. In terms of information entropy, Retinex and Retinex-Net have improved different X-ray images to a certain extent. This algorithm is superior to the two algorithms in improving the information entropy. This is very significant, which can make the image retain more information. For the average gradient, The average gradient of the enhanced Retinex algorithm is lower than that of the original image, which indicates that the Retinex is overexposed and reduces the average gradient of the image. Retinex-Net increases the mean gradient, but it is not very significant. The algorithm in this paper is very effective to improve the average gradient. It can greatly enhance the detail information of X-ray images and improve the practical application ability of X-ray images. Various actual information entropy and mean gradient experimental data are shown in Table I.

V. CONCLUSION

Due to the complex imaging environment and more interference, X-ray images have many problems, such as too much noise and insufficient detail information, which are inconvenient in practical application. In order to solve the problems existing in the practical application of X-ray images, This paper uses Retinex-Net model to enhance X-ray image by combining weighted guided filter and local detail enhancement algorithm. Firstly, the X-ray image is decomposed into irradiation and reflection components by a decomposition network in the Retinex-Net model. Secondly, the radiation component is enhanced by an enhanced network. Thirdly, the noise is removed from the reflected component by the weighted guided filter algorithm, and then the detail information in the reflected component is enhanced by the local detail enhancement algorithm. Finally, the enhanced X-ray image is obtained by multiplying the enhanced irradiation component and the reflected component. The experimental results show that the algorithm can effectively improve the visual effect and contrast, enhancing detail information while suppressing noise, and avoid halo artifacts. Moreover, this algorithm can adjust parameters automatically and enhance quickly, so it is very effective in the practical application of X-ray images. In the future, we will focus on the details of small targets in X-ray images, in order to contribute to the detection and recognition of small targets in X-ray images.

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