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Medical Image Enhancement Using Recurrent Neural Networks Based Tv Homomorphic Filter

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Abstract: Image Enhancement is one of the important requirements in Digital Image Processing which is important in making an image useful for various applications which can be seen in the areas of Digital photography, Medicine, Geographic Information System, Industrial Inspection, Law Enforcement and many more Digital Image Applications. Image Enhancement is used to improve the quality of poor images.

X-ray image contains a large amount of information and became important basis in the process of medical diagnosis. The X-ray image has large gray dynamic range but low contrast. This work proposed a new kind of homomorphic filter with ANN which uses total variation model as the transfer function. It has a good balance in both brightness adjustment and details enhancement. And the comparison results were given, the experimental results show that the method can effectively increase the image contrast, highlight the details.

Index Terms: Medical image; X-ray image; total variation (TV); image enhancement; image de-noising; ANN

I. INTRODUCTION

Image enhancement process consists of a collection of techniques that are used to improve the visual appearance of an image. Image enhancement is a process by which the visual quality and the overall appearance of an image are improved so as to extract the spatial features of the image.

The X-ray has been widely used in the biomedical and medical fields since it was born. At present, X-ray images have become important basis in the process of medical diagnosis. Medical X-ray image contains a large amount of information, but the details are fuzzy and the contrast is low, which makes adverse effects on the doctor's judgment.

Thus improving the image contrast and enhancing the details sharpness while suppressing the noises are the key points of this kind of image enhancement with the birth and development of digital X-ray image equipment, storage, transmission and processing of medical

X-ray images are more convenient. It leads to that digital X-ray image enhancement algorithms have been more and more researched and applied. The common X-ray image enhancement methods can be divided into two types, which can be summarized as following: Histogram Equalization (HE) is a useful method of image enhancement. In the practical application, researchers [1-3] put forward a series of improved algorithm to achieve better, results. Pizer et al. [4] carried local analysis on HE algorithm and proposed the Adaptive Histogram Equalization (AHE). AHE uses local window sliding upon the image and calculates the local gray-level histogram distribution to obtain the gray-level mapping of the window center pixel.

This method could make full use of the neighborhood information; however, it is sensitive to the noise and prone to local enhancement phenomena. Zuiderveld [5] put forward an improved algorithm called Contrast Limited Adaptive Histogram Equalization (CLAHE) on the basis of AHE. CLAHE uses a amplitude limiting method to prevent local over-enhancement. Its effect is remarkable when applied in the medical X-ray image enhancement.

Retinex is a kind of image enhancement method based on human visual characteristics, it was put forward by Edwin H.L in 1963 [6], Retinex theory defines that the color of the object is determined by the light reflection ability of red wave, green wave, and blue wave, rather than determined by the absolute value of reflected light intensity. Namely, color of an object is not affected by light heterogeneity. Retinex is based on color constancy, It can realize the dynamic range compression and edge enhancement. Retinex algorithm developed from single-scale Retinex(SSR) to multi-scale Retinex(MSR). MSR algorithm can effectively change the image grey distribution, improve the contrast of image, thus it is used in X-ray image enhancement [7].

II. IMAGE ENHANCEMENT

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide better input for other automated image processing techniques. Image Enhancement (IE) transforms images to provide better representation of the subtle details. It is an indispensable tool for researchers in a wide variety of fields including (but not limited to) medical imaging, art studies, forensics and atmospheric sciences. It is application specific: an IE technique suitable for one problem might be inadequate for another.

For example forensic images or videos employ techniques that resolve the problem of low resolution and motion blur while medical imaging benefits more from increased contrast and sharpness. Thus, for example, a method that is quite useful for enhancing X-ray images may not be the best approach for enhancing satellite images taken in the infrared band of the electromagnetic spectrum.

There is no general —theory of image enhancement. When an image is processed for visual interpretation, the viewer is the ultimate judge of how well a particular method works.

Producing digital images with good brightness/contrast and detail is a strong requirement in several areas like vision, remote sensing, biomedical image analysis, fault detection. Producing visually natural images or transforming the image such as to enhance the visual information within, is a primary requirement for almost all vision and image processing tasks. Methods that implement such transformations are called image enhancement techniques. The task of image enhancement is a difficult one considering the fact that there is no general unifying theory of image enhancement at present, because there is no general standard of image quality that can serve as a design criterion for an image enhancement processor. Most of the enhancement techniques in existence to date are empirical or heuristic methods, dependent on the particular type of image.



Figure 1: (a) Original image (b) Enhanced Image

More important, most of these techniques require interactive procedures to obtain satisfactory results, and therefore are not suitable for routine application. Besides requiring the user interaction, many such methods require specification of external parameters, which sometimes are difficult to fine-tune. Finally, the enhancement methods most widely employed treat the spatial information in the image in a global fashion, while in many cases it is necessary to adapt the transformation to the local features within different regions of the image.

The Image enhancement techniques can be divided into three broad categories:

- 1) Spatial domain methods, which operate directly on pixels, and
- 2) Frequency domain methods, which operate on the Fourier transform of an image. Spatial operations are performed directly on the pixels of a given image. We classify spatial operations into three broad categories:
- 3) Single pixel operations The simplest operation we perform on a digital image is to alter the values of its individual pixels based on their intensity. This type of process may be expressed as a transformation function, T of the form:

$$s = T(z) \tag{1}$$

Where z is the intensity of a pixel in the original image and s is the (mapped) intensity of the corresponding pixel in the processed image.

4) Neighborhood Operations

Neighborhood operations are those that combine a small area or neighborhood of pixels to generate an output pixel. The most important neighborhood operator is convolution. To convolve something means to roll together. In digital imagery, this means that a local area of pixels is combined in various ways to achieve some desired result. Almost as important as convolution is the process of sampling.

Many neighborhood operators result in sub pixel addressing, which means that data values that exist between the discrete pixels of a digital image must be derived. Different methods for sampling allow this to occur. The applications of neighborhood operators are many, ranging from digital filters to techniques for sharpening, transforming, and warping images. When implementing the point operations, it is possible to perform a given function and, if desired, save the resulting pixels in the same memory buffer, thereby destroying the original input pixels. For point operations this is allowable, because once an input pixel has been processed its original value is no longer needed. This is not possible with neighborhood operators because, even after an output pixel has been calculated, the corresponding input pixel at that location is included in other neighborhoods. Therefore no input pixels can be overwritten until all relevant output pixels have been calculated.

5) Geometric spatial transformations and image registration

Geometric transformations modify the spatial relationship between pixels in an image. A geometric transformation consists of two basic operations:

- a) A spatial transformation of coordinates, and
- b) Intensity interpolation that assigns intensity value to the spatially transformed pixels.

The transformation of coordinates may be expressed as:

$$(x,y) = T \{(v,w)\} \quad (2)$$

Where (v,w) are pixel coordinates in the original image and (x, y) are the corresponding pixel coordinates in the transformed image.

For example, the transformation

$$(x,y) = T \{(v,w)\} = (v/2,w/2) \quad (3)$$

shrinks the original image to half.

III. LITERATURE SURVEY

WANG Zhiming, TAO Jianhua [8] in “A Fast Implementation of Adaptive Histogram Equalization” discussed Adaptive Histogram Equalization (AHE) is a popular and effective algorithm for image contrast enhancement. But it's quite computationally expensive and time consuming.

In this paper, a fast implementation of AHE based on pure software techniques is proposed. Three accelerative techniques are combined to form the new fast AHE: First, local histogram is acquired by an iterative approach with a sliding window; Second, in computing cumulative histogram function, not more than half of the histogram is cumulated; Third, by keep the block size W^2 equal to the product of grey level number and integral power of 2, all the multiplication and division operations are replaced with fast bitwise shift.

H.D. Cheng and X.J. Shi [9] in “A simple and effective histogram equalization approach to image enhancement” discussed one of the most commonly used methods is histogram equalization (HE). The main idea of HE-based methods is to re-assign the intensity values of pixels to make the intensity distribution uniform to utmost extent [5]. Suppose that the original image is normalized and the range of its intensities is $[0, 1]$, and $p(x)$ is the density function of intensity distribution of the original image, where x denotes the intensity value of the normalized image.

Henan, Wu *et al.* in 2011 presented an enhancement algorithm predicated on multi-scale Retinex to be able to improve the potency of remote sensing image enhancement. The principle and recognition types of multi-scale Retinex and wavelet were calculated. The research of panchromatic and multicolor remote sensing image enhancement were agreed out on the basis of the two methods, the end result showed that the mean value of enhanced image by this algorithm is all about 125, the entropy and definition might be improved by 5% and 25% in contrast to wavelet algorithm, and remote sensing images might acquire better enhancement quality, so multi-scale Retinex is a superior method for sensing image enhancement.

Juliastuti, E *et al.* in 2012 evaluated the contrast quality of digital image that scanned using both mode based on statistic image characteristic. The outcomes showed that the quality of digitized image using transmission mode is preferable to using reflection mode. However, if direct digital imaging is employed as a gold standard, image enhancement on digitized image continues to be necessary.

Hasikin, Khairunnisa *et al.* in 2012 presented a fuzzy grayscale enhancement technique for low contrast image. The humiliation of the low contrast image is normally caused by the insufficient lighting during image capturing and thus ultimately generates non-uniform illumination in the image. The majority of the developed contrast enhancement techniques enhance the image quality without thinking about the non-uniform lighting in the image. The fuzzy grayscale image enhancement method is proposed by maximizing fuzzy events contained in the image. The membership function is then adapted to improve the image by utilizing power-law transformation and saturation operator. The proposed method produced better quality enhanced image and required minimum processing time compared to other methods.

Mohammad F. K *et al.* in 2012 presented Bi histogram and Multi Histogram methods. Bi HE approach enhances the contrast preserving the brightness of the image but it spoil the natural display of image. On the contrary, Multi HE methods preserve the natural display but can't maintain the intensity or contrast. Firstly, the histogram of input image is divided into different sectors and then HE is applied on every sector. Each section is known as sub-histogram. It reduces the decomposition error of input histogram. Wang, Lung-Jen *et al.* in 2012 showed that nonlinear image enhancement may be used to increase the quality of a fuzzy image. The aim of this paper is to build a successful image classification technique to determine the very best mix of clipping and scaling parameters by the chance cost method for image enhancement. Experimental results gives idea about the proposed opportunity cost method with image classification for the nonlinear image enhancement achieves a much better subjective and objective image quality performance compared to method utilizing the opportunity cost without image classification and other nonlinear image enhancement methods [17,18].

Peng, Zhang *et al.* in 2013 proposed a multi-scales nonlinear enhancement method of THz image. The THz image has lower contrast and bigger noise because the THz radiant power is small, for the purpose of improving the image definition. The detail coefficients are taken to de-noise and histogram equalization to be able to enhance this is of image edge and image detail. The approximation coefficients are taken to nonlinear transform to be able to suppress the background noise and improve target information. The proposed method could boost up the prospective information of THz image and take away the noise of THz image at the same time. Accordingly the brand new method could increase the THz image definition, and avoid the phenomenon that the histogram equalization not just enhances the prospective information but moreover enhances noise. Theory analysis and experiment shows that the brand new method is realistic and efficient, and the THz image enhancement effect is more matching the character of human eye. Khairunnisa H. *et al.* in 2013 have presented a fuzzy based technique for low contrast and non uniform images. The fuzzy method differentiates the dark and bright parts of the image. The fuzzy based technique outperforms the other conventional enhancement techniques such as power law transformation. Also, it produces brighter images and takes less time to implement as compared to other techniques. It has been proved that the processing time of the Fuzzy approach is 100ms.

Bhattacharya. S *et al.* in 2014 have proposed a fast method called singular value decomposition (SVD) to improve the contrast of an image locally. The image enhancement is used to increase the visual information of an image using various steps such as contrast enhancement, deblurring, denoising etc. Contrast Enhancement is the most vital part of image enhancement because human eye is more sensitive to luminance than the chromatic information of an image. Mostly, the contrast enhancement techniques focus on the global enhancement of images but such global methods lead to loss of information in images. Thus, a technique is required to carry out localized image enhancement.

IV. CLAHE

A generalization of adaptive histogram equalization called contrast limited adaptive histogram equalization, also known as CLAHE, was developed to address the problem of noise amplification. CLAHE operates on small regions in the image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image. CLAHE was originally developed for medical imaging and has proven to be successful for enhancement of low-contrast images such as portal films.

The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This evens out the distribution of used grey values and thus makes hidden features of the image more visible. The full grey spectrum is used to express the image. Contrast Limited Adaptive Histogram Equalization, CLAHE, is an improved version of AHE, or Adaptive Histogram Equalization, both overcome the limitations of standard histogram equalization.

A variety of adaptive contrast-limited histogram equalization techniques (CLAHE) are provided. Sharp field edges can be maintained by selective enhancement within the field boundaries. Selective enhancement is accomplished by first detecting the field edge in a portal image and then only processing those regions of the image that lie inside the field edge. Noise can be reduced while maintaining the high spatial frequency content of the image by applying a combination of CLAHE, median filtration and edge sharpening. This technique known as Sequential processing can be recorded into a user macro for repeat application at any time. A variation of the contrast limited technique called adaptive histogram clip (AHC) can also be applied. AHC automatically adjusts clipping level and moderates over enhancement of background regions of portal images.

V. RECURRENT NEURAL NETWORK

RNNs are a sort of neural network that is both strong and robust, and they are one of the most intriguing algorithms being used because they are the only ones having an internal memory.

Recurrent neural networks, like so many deep learning techniques, are relatively new. They were first developed in the 1980s, but it wasn't until recently that we realised their full potential. RNNs have risen to prominence as a result of increased computer power, vast amounts of data we now have to deal with, and the advent of long short-term memory (LSTM) in the 1990s.

RNNs can recall critical details about the input they receive thanks to their internal memory, allowing them to anticipate what will happen next with great accuracy. This is why they're the chosen algorithm for time series, speech, text, financial data, audio, video, weather, and many other types of sequential data. In comparison to other algorithms, recurrent neural networks can acquire a far deeper grasp of a sequence and its context.

RNNs (recurrent neural networks) are a type of neural network that can be used to model sequence data. RNNs, which are derived from feedforward networks, behave similarly to human brains. Simply said, recurrent neural networks can anticipate sequential data in a way that some other approaches can't.

You'll need a basic understanding of "regular" feed-forward neural networks and sequential data to fully comprehend RNNs.

Sequential data is simply structured data during which related items appear one after the other. Financial data or even the DNA sequence are two instances. Perhaps the most common sort of sequential data is time series data, that is just a collection of data points in chronological order.

The way RNNs and feed-forward neural networks channel information gives them their names.

The information in a feed-forward neural network only flows in one way from the input layer towards the output layer, passing through into the hidden layers. The data travels in a straight line and through network, never passing through the same node twice. Feed-forward neural networks have no recollection of the information they receive and are poor predictors of what will happen next. A feed-forward network has no concept of time order because it only analyses the current input. Except for its training, it has no recollection of what transpired in the past.

The information in an RNN cycles via a loop. When it makes a judgement, it takes into account the current input as well as what it has learnt from prior inputs.

The knowledge transfer between an RNN and a feed-forward neural network is depicted in the two figures below.

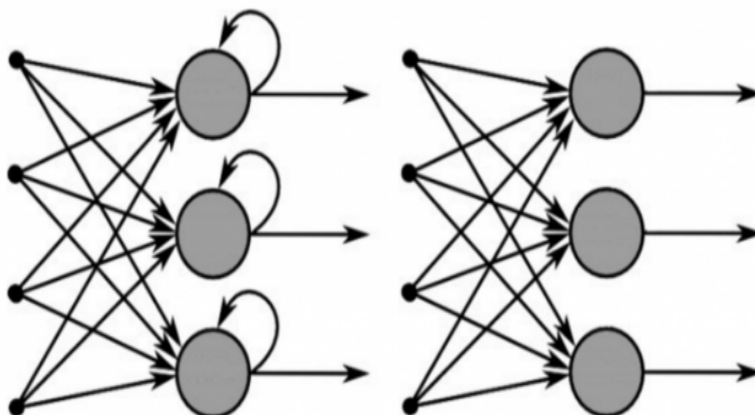


Figure 2: RNN's and feed-forward Neural Networks

VI. PROPOSED PRINCIPLE

A. Homomorphic Filter

Homomorphic filter is a kind of frequency domain image contrast enhancement and image brightness range compress method. Homomorphic filter can reduce the low frequency and increase the high frequency information, thus it can reduce the illumination change and sharpen edges and details.

Image homomorphic filtering is on the basis of incident and reflected light model. If the image function $j(x, y)$ is expressed as the illumination function, namely, as the product of the incidence component $i(x, y)$ and reflect component $r(x, y)$, so the image model can be expressed as:

$$F(x,y)=i(x,y).r(x,y) \tag{4}$$

$r(x,y)$ depends on the surface of an object. the incident component generally stands for the constant component of gray, and is equivalent to the low frequency information of frequency domain, then weakening incident light can narrow the scope of image gray level; while reflect component is closely related to the boundary of the object characteristics, and equivalent to the high frequency information, then strengthening the reflected light can improve the image contrast. The progress can be described as Fig.3.

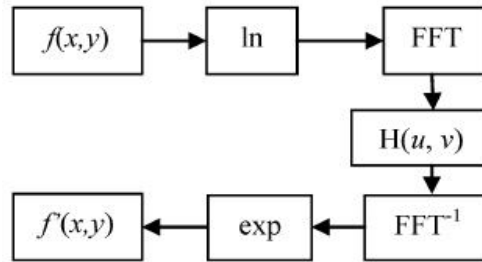


Figure 3: Frequency domain homomorphic filter

The steps to realize the homomorphic filtering are as following:

- 1) Do the logarithm operation on the original image as (2), it can change the multiplication " • " into simple addition:

$$Z(x,y)=\ln f(x,y)= \ln i(x,y)+\ln r(x,y) \tag{5}$$

- 2) Do the Fourier transforms on both size of (2), then:

$$Z(u,v) = \ln i(u,v)+\ln r(u,v) \tag{6}$$

Where Z , I and R are the Fourier transforms of z , i and r respectively. The function Z represents the Fourier transform of the *sum* of two images: a low frequency illumination image and a high frequency reflectance image.

- 3) Apply a filter with a transfer function H which is usually a high-pass filter that suppresses low frequency components and enhances high frequency components, then we can suppress the illumination component and enhance the reflectance component.

$$S(u,v)=Z(u,v)H(u,v) \tag{7}$$

- 4) Do Fourier inverse transformation operation on S reflectance component.

$$s(x, y)= \mathcal{F}^{-1}[S(u, v)] \tag{8}$$

- 5) Obtain the filtered image $g(x, y)=\exp[s(x, y)]$.

B. Total Variation

Total variational(TV) model is first proposed by Rudin, Osher and Fatemi [8], [9], also known as ROF model. It is widely used in image restoration and image denoising. Assuming the noise image as $u_0(x, y)$, the clear image as $u(x, y)$, noise as $n(x, y)$, then:

$$u_0(x, y) = u(x, y) + n(x, y) \tag{9}$$

The TV denoising model is actually a nonlinear filter based on solving the partial differential equation (PDE), aiming to enhance $u(x, y)$ and reduce $n(x, y)$. The TV of image $u(x, y)$ is:

$$TV(u)=\int_{\Omega} |\nabla u| d\Omega \tag{10}$$

$|\nabla u| = \sqrt{u_x^2 + u_y^2}$; Ω is the boundary of the image $u(x, y)$.

The noise reduction can be transferred to the process of the total variation minimization problem: i.e. to solve $\min\{TV(u)\}$, then it can establish an equivalent energy functional as following:

$$E(u) = \|u_0 - u\|^2 + \lambda \int_{\Omega} |\nabla u| d\Omega \tag{11}$$

The Euler-Lagrange equation for (11) is:

$$(u - u_0) - \lambda \operatorname{div}(\nabla u / |\nabla u|) = 0 \tag{12}$$

We make TV model take the place of $H(u, v)$ in homomorphic filter as a new transfer function. Here we use (4) as the original image function; and after the logarithmic transformation on both sides of equation (4), we obtain (5).

The purpose of image enhancement is to increase and reduce i . If we assume $u_0(x, y) = \ln(f(x, y))$, $u(x, y) = \ln(r(x, y))$, $n = \ln(i(x, y))$. The TV model can be used as a homomorphic filter transfer function. And the restored $u(x, y) = \ln(r(x, y))$ can be obtained by using (11) and (12). The final result $g(x, y) = \exp[u(x, y)]$. The progress of homomorphic filtering based on TV is shown as Fig. 4.

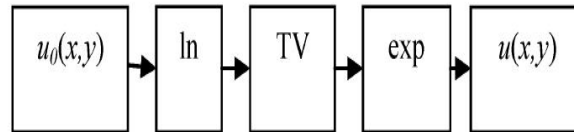


Figure 4: TV homomorphic filter.

VII. RESULT AND DISCUSSION

We chose two groups of X-ray image results: the one is chest X-ray image, it is common and representative because it includes bones, tissues and gas; the other is foreign body X-ray image, it includes organs and foreign body. In order to evaluate the quality of the image objectively, we applied the mean value, image entropy, average gradient and average Laplacian in evaluating the results. In paper [8,16], the image entropy can effectively evaluate the image quality. The entropy of an image is defined as:

$$S = -\sum_{i=1}^L p_i \ln p_i \tag{13}$$

Where P_i is the frequency of occurrence of pixels at i^{th} grey level, $i = 1, 2, \dots, L$. When the brightness of two images are similar, the larger the entropy, the better the image quality.

The clearer the image is, the sharper the edge is, Thus the average gradient and average Laplacian [9] could be used as the evaluate function, The larger the average gradient or the average Laplacian is, the better the image quality is.

The average gradient is defined as:

$$D = \frac{\sum_{i=1}^M \sum_{j=1}^N [I(i+1, j+1) - I(i, j)]^2}{MN} \tag{14}$$

The Laplacian is commonly used as in the edge detection while is defined as:

$$L = \frac{\sum_{i=1}^M \sum_{j=1}^N [I(i+1, j) + I(i-1, j) + I(i, j+1) + I(i, j-1) - 4I(i, j)]}{MN}$$

Table 1: Evaluation Results of Sonography.jpg

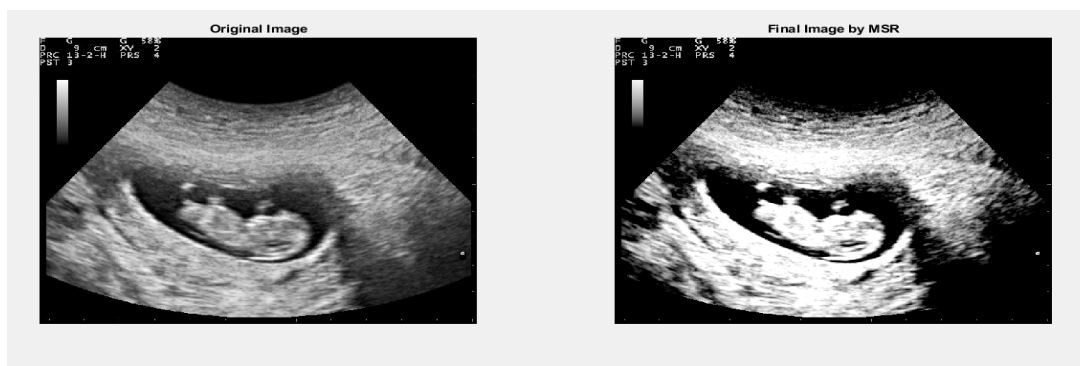
Graphics	Original	CLA HE	MSR	TV HPF	RNN+TV HPF
Mean value	76.23 61	140.8 137	120.86 87	164.70 84	152.9016
Entropy	5.934 6	10.51 40	9.0509	12.192 1	18.4038
Average Gradient	28.70 20	60.74 84	1.0847 e+04	92.004 3	180.3669
Average Laplacian	2.064 2	11.22 13	131.53 36	5.9757	17.9881

Table 2: Evaluation Results of X-ray.jpg

Graphics	Original	CLAHE	MSR	TV HPF	RNN+TVHPF
Mean value	155.178	163.992	213.0391	302.979	310.3597
Entropy	7.3038	8.6371	10.0486	13.0080	21.9876
Average Gradient	19.3848	49.1715	2.2440e+03	78.2551	150.7244
Average Laplacian	0.5181	7.5656	3.1008	2.2540	6.1678



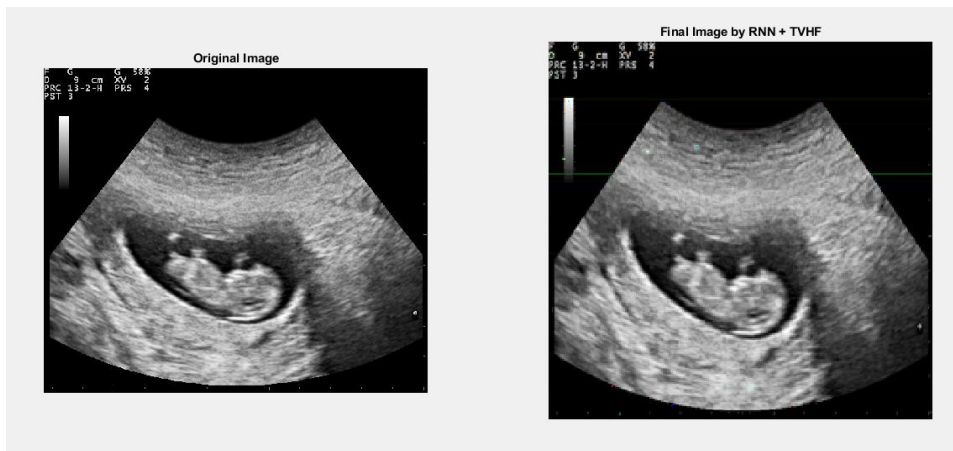
(a)



(b)

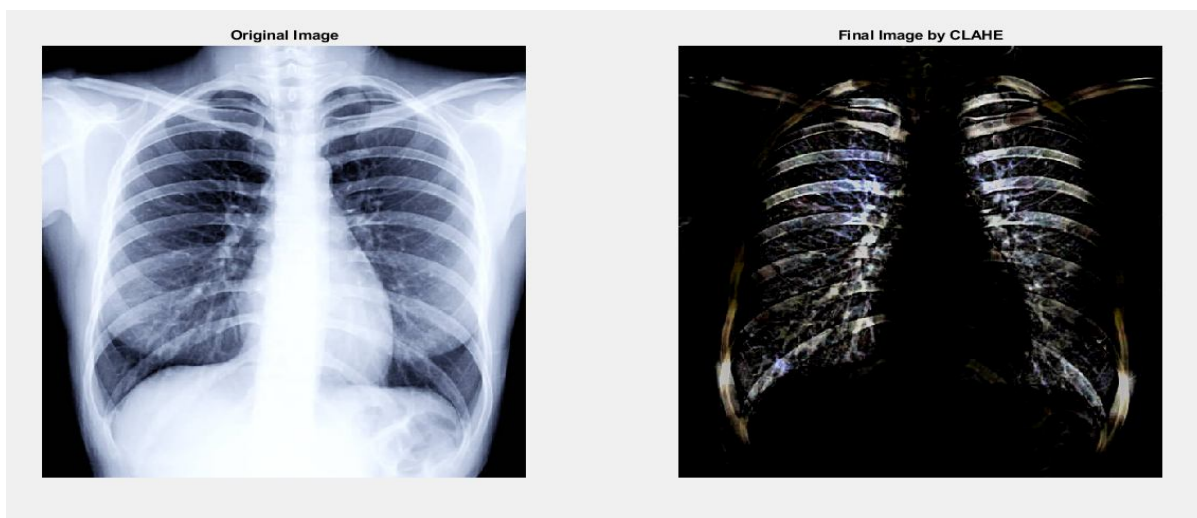


(c)

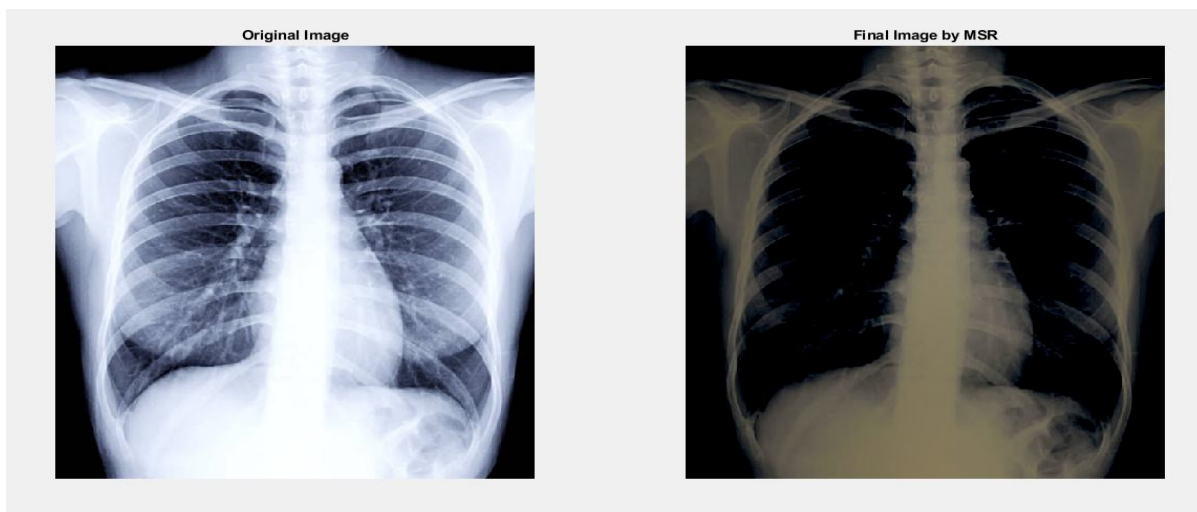


(d)

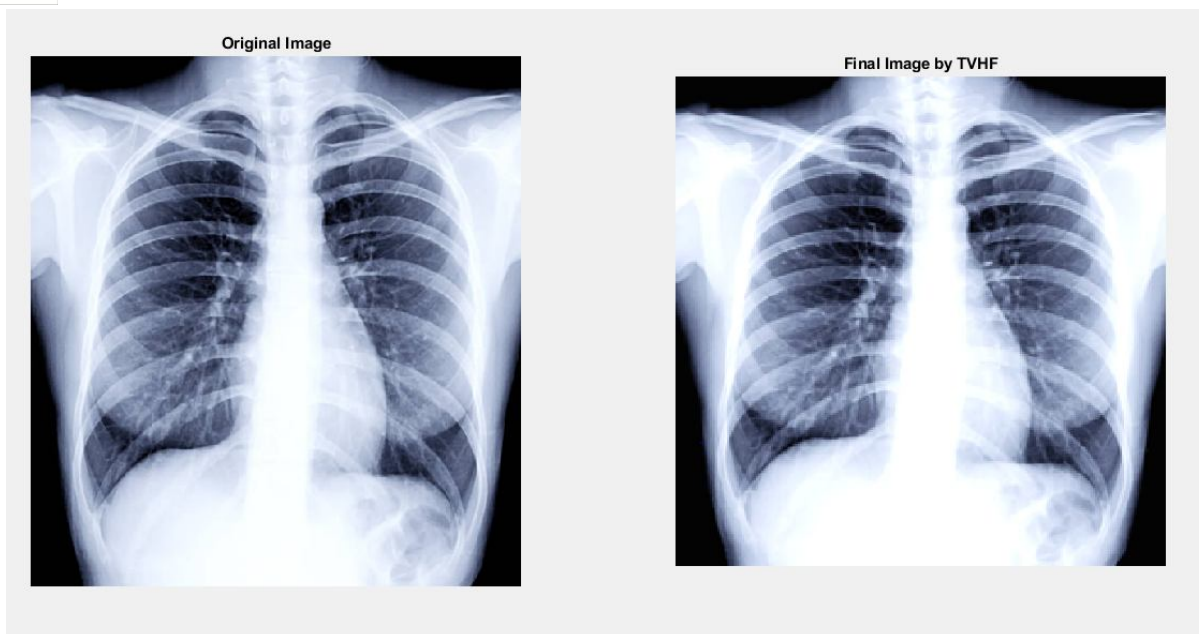
Figure 5: Column (a) are the results by CLAHE, column (b) are the results by MSR, column(c) are the results by TVhomomorphic filter, column (d) are the results by TVhomomorphic filter.+ RNN



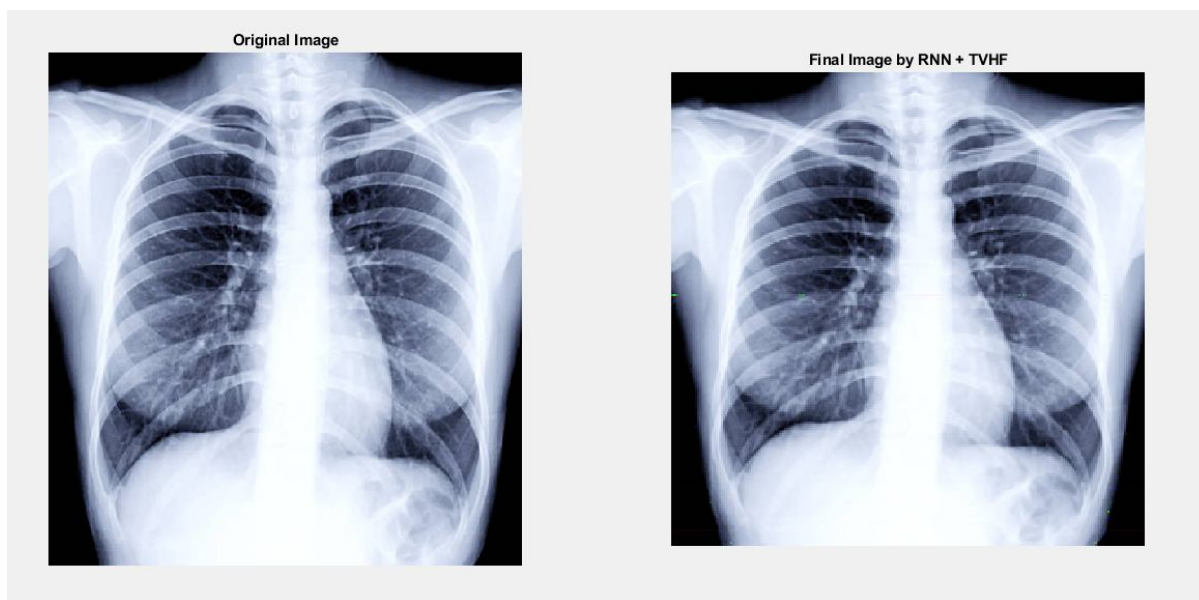
(a)



(b)



(c)



(d)

Figure 6: Column (a) are the results by CLAHE, column (b) are the results by MSR, column(c) are the results by TVhomomorphic filter, column (d) are the results by TVhomomorphic filter.+ RNN

The results show that all the tree methods could enhance the image contrast. Both the Subjective visual feeling and the objective evolution value can prove, they are effective for X-ray image[15-16].

Rtinx method calculates the background together. It can be noted that the CLAHE method plays a good performance on contrast adjustment, and the entropy value shows the globe image quality is better than our method. Meanwhile our method has advantage in details enhancement.

VIII. CONCLUSION

Medical image enhancement is a necessary and important research because it is the basis for the doctor diagnosis. But during the imaging progress, Sonography, X-ray image digressed by the influence of imaging system. It has a large gray dynamic range, but its details are covered in the tiny gray dynamic range.

Homomorphic filter is mainly used to reduce the uneven illumination and enhance the image quality, it belongs to the frequency domain processing by using a frequency transfer function, the problem is the transfer function reduce the low frequency as well as lose gray information at X-ray image dark space. This work proposed a new homomorphic filter using the TV model as transfer function, it has a good balance in both brightness adjustment and details enhancement. The results show that TV-homomorphic filter with RNN is effective for medical image enhancement.

REFERENCES

- [1] Kim T, Paik J, "Adaptive contrast enhancement using gaincontrollable clipped histogram equalization." IEEE T Consum Electr,2008,54(4),pp 1803-1810
- [2] Ibrahim H,Kong NSP, "Brightness preserving dynamic histogram equalization for image contrast enhancement." IEEE T Consum Electr 2007,53(4),pp 1752-I 758.
- [3] Pizer S. "Adaptive histogram equalization and its variations ". Computer Vision, Graphics and Image Processing, 1987, 39(3), pp.355-368.
- [4] K. Zuiderveld. "Contrast Limited Adaptive Histogram Equalization. " In : P. Heckbert: Graphics Gems IV, Academic Press 1994
- [5] Edwin.H.Land ."The Retinex Theory of Color Vision." ScientificAmerican, 1977(237), pp 108-128.
- [6] Wang Z, Wei J. "Image enhancement of X-ray film base on mutilscale retinex." Artificial Intelligence and Computational Intelligence. Berlin Heidelberg, 2011 , pp.411-417.
- [7] Kovasznyay, L.S.G., Joseph H.M., "Image Processing", Proceedings of the IRE, vol. 43, issue 5, pp. 560-570, May 1955.
- [8] Collins, S., Wade, M. "A critical review of analog image processing", IEEE Colloquium on Integrated Imaging Sensors and Processing, pp. 1/1-1/6, December 1994.
- [9] Mr.M.Venkatesan, Mrs. P.MeenakshiDev, Dr. K.Duraiswamy and Dr.K.Thyagarajah "Secure Authentication Watermarking for Binary Images using Pattern Matching", IJCSNS International Journal of Computer Science and Network Security, vol.8, issue 2, pp. 241-250, February 2008.
- [10] D. Kunder and D. Hatzinakos, "Blind Image Deconvolution", IEEE Signal Processing Magazine, pp. 61-63, November 1996.
- [11] Rupali Patil and Sangeeta Kulkarni, "Blurred Image Restoration Using Canny Edge Detection and Blind Deconvolution Algorithm", International Journal of Computer Technology and Electronics Engineering (IJCTEE), pp.10-14, March 2011.
- [12] D. Srinivasa Rao, K. Selvani Deepthi and K. Moni Sushma Deep, "Application of Blind Deconvolution Algorithm for Image Restoration", International Journal of Engineering Science and Technology, Vol. 3, issue 3, pp. 1878-1884, March 2013.
- [13] Zohair Al-Ameen, Ghazali Sulong and Md. Gapar Md. Johar, "A Comprehensive Study on Fast image Deblurring Techniques", International Journal of Advanced Science andTechnology, Vol. 44, pp. 1-10, July, 2012.
- [14] Yogesh K. Meghrajani and Himanshu Mazumdar, "An Interactive Deblurring Technique for Motion Blur", International Journal of Computer Applications, Vol. 60, issue 3, pp. 887-975, December 2012.
- [15] Mohammad Qatawneh, YacoubMassad, Mohammed Musaddaq, Tawfiq Khalil and AzzamSleit, "A Uniform Noise Median Filter Based on a New Type of Filtering Window", International Journal of Computer Applications, Vol. 84, issue 16, pp. 412- 417, December 2011.
- [16] Mr. RohitVerma and Dr. Jahid Ali, "A Comparative Study of Various Types of Image Noise and Efficient Noise Removal Techniques", International Journal of AdvancedResearch in Computer Science and Software Engineering, Vol. 3, Issue 10, pp. 617-622, October 2013.
- [17] M. M. Siddiqui, "Some Problems Connected With Rayleigh Distributions", Journal of research of the National Bureau of Standards, vol. 66D, issue 2, pp. 167-174, March- April 1962.
- [18] Shabnam Sultana, M.Varun Kumar and N.Asha, "Comparison of Image Restoration and Denoising Techniques", International Journal of Advanced Research in ComputerScience and Software Engineering", Volume 3, Issue 11, pp. 337-341, November 2013



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