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ENHANCEMENT OF X-RAY IMAGES FOR LUNG DISEASES DETECTION

[1]Amrutha T M, Anoop S Pillai[2]

[1]PG Scholar, Department of Electronics and Communication Engineering, NSS College of Engineering, Palakkad
[2]Associate Professsor, Department of Electronics and Communication Engineering, NSS College of Engineering, Palakkad

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Abstract –X-ray image inspection is an important part of medical diagnostics. However, because of the poor contrast and dynamic range of an X-ray, key features such as organs, bones, and nodules might be difficult to spot. As a result, contrast adjustment is crucial, particularly because it can enhance features in both bright and dark areas. As a result, we present a new approach based on component attenuation for X-ray picture enhancement. An X-ray image could be broken down into tissue components and important details. Because tissues aren't always the primary focus of an X-ray, we proposed using adaptive tissue attenuation and dynamic range stretching to improve visual contrast. A parametric correction approach was developed using component decomposition and tissue attenuation to provide several enhanced images at once. Finally, a framework for combining these augmented images and providing a high-contrast output in both bright and dark regions was developed.

Index Terms—X-ray image enhancement, component attenuation, parametric contrast adjustment model.

1.INTRODUCTION

X-ray image inspection is a key stage in medical diagnosis. However, the low contrast and dynamic range of an X-ray image make it difficult to distinguish these anatomical parts immersed in the high and low contrast regions. The high contrast parts of an X-ray image are significant because they contain numerous vital organs and bones. Small but significant elements, such as nodules, on the other hand, are frequently visible dark areas. A higher dynamic range is required to properly distinguish both the bright and dark regions in order to identify organs and nodules at the same time. It's difficult to see features in a regular and low-dynamic range (LDR) X-ray image without augmentation .

Fig. 1 shows example of X-ray scans provided by a local hospital. These visuals have a low contrast and dynamic range, making it difficult to identify details and establish a precise diagnosis. To aid with this, we offer an ensemble framework for X-ray image enhancement that includes tissue attenuation, contrast control, and image fusion.

Our technique seeks to vividly portray the features of LDR X-ray images by boosting the contrast in bright and dark regions.

Fig -1: Two typical X-ray images in our testing dataset. The images have low dynamic ranges. Their bright and dark regions also show low contrast.

2.LITERATURE REVIEW

For increasing image contrast and details, a variety of image enhancement approaches have been developed. The global tone mapping methods use a mapping function to convert input intensity values into new values while increasing global contrast, however one disadvantage is that image details may be lost.

Local adaptive tone mapping approaches, on the other hand, use spatially variable transfer functions to improve contrast details [3], [4]. The outcomes, on the other hand, may have unfavourable negative effects. As a result, preserving spatial consistency after local patch enhancement is critical. In order to improve local contrast, the Retinex theorem [5] advises suppressing illumination bias [6]–[8]. These Retinex-based approaches can improve results in low-light or gloomy environments. When working with bright locations, however, the resultant contrast is usually low. Furthermore, the improved outcomes frequently have halo impacts and appear artificial. Transform-based approaches, on the other hand, add alterations to an image (for example, the DCT-discrete cosine transform or the wavelet transform). The enhancement techniques are then used to modify the coefficients in a transform domain. Finally, an inverse transform is used to create a complete enhanced image. Despite the fact that transform-based approaches can provide global and local contrast augmentation, the end results may have halo effects. Several edge-preserving approaches, such as bilateral filtering [11], have subsequently been merged with transform-based techniques to eliminate halo effects.

We'll go through several relative and representational enhancement approaches to help you comprehend things better. Global tone mapping approaches include gamma correction [2], S-curve correction [12], and histogram equalisation [2]. Gamma correction methods can expand image contrast in either dark or bright places by manually setting the gamma parameter of the global mapping function. S-curve correction methods are based on the same principle as gamma correction. S-curve correction approaches, on the other hand, enable additional manual tuning settings, allowing a system to apply an S-shaped global mapping function to enhance both dark and bright regions simultaneously. Histogram equalisation (HE) [2] and multi-scale HE [13] on the other hand, strive to automatically determine the global mapping function by maximising the augmented image's histogram entropy. When the histogram allocation has peaks, HE-based algorithms are efficient, but they like to unduly enhance an image and produce strange artefacts. Finally, current global tone mapping approaches are unable to enhance local image regions in an adaptable manner.

2D-histogram-based mapping techniques [14]–[16] that use contexture information from nearby patches have recently been developed to improve local contrast. They are based on the premise that increasing the graylevel difference between a neighbouring pixels will boost image local contrast. As a result, the author constructed a 2D histogram in [14] to track the incidence of gray-level pairs within a small area. A mapping function could be created to equalise the 2D histogram in such a way that the intensity differences between surrounding pixel sets are spread equitably. CVC [15] is an enhanced version of [14]. In addition to needing a uniform target histogram, CVC incorporated a differential term to smoothing the target histogram. By mapping the diagonal components of the original 2D histogram of the input data to the diagonal components of the 2D target histogram, the final mapping function may be achieved. A more sophisticated objective function for estimating the target histogram was given in [16]. Aside from the requirement for a uniform distribution, higher level image factors have smoothness restrictions as well as smoothness constraints being considered at the same time. These changes could be beneficial. Provide more satisfying outcomes. The calculation, on the other hand, the price is exorbitant. In contrast, [17] and [18] advocated a hybrid technique combining global mapping with transform-based augmentation. SECEDCT, a spatial entropy-based contrast enhancement technique in DCT, was introduced in [17]. The spatial entropy of various gray-level intensities was defined and calculated over an image. The global contrast enhancement function, which transfers the source intensity to an output value, was then derived using the spatial entropy function. Furthermore, 2D-DCT was employed to convert the global improved image into the frequency domain in order to accomplish local contrast augmentation. While SECEDCT can improve image contrast, it does not allow the system to manage global contrast or retain image brightness. The authors have offered a revised version [18] to address these concerns. Image sharpening and dynamic range compression can also be accomplished using Retinex-based algorithms. By estimating the intensity ratio between a pixel and its surroundings, Single-Scale Retinex (SSR) [8] increases visual contrast. The filter scale must be chosen through trial and error to achieve a better outcome. Multi-Scale Retinex (MSR) [9] was also developed to combine numerous SSR-enhanced results created under different filter scales to balance dynamic compression and image rendering.

Methods based on retinex and methods based on transform have a connection. An input image is decomposed into base layers (low-frequency components) and detail layers in both approaches (high-frequency components) .The image details can be recognised by attenuating the base layers or enhancing the detail layers. In the literature, different decomposition strategies have been discovered. Choi et al. [19], Durand and Dorsey [20] enhanced an image with only one base layer and one detail layer, whereas [21]–[24] examined numerous base and detail layers for enhancement. Linear functions were employed to compress the base layers in the original intensity domain [21], [22]. Instead, [23], [24] used nonlinear functions in the feature domain to condense the dynamic range. Some ensemble frameworks have recently been presented to increase image quality. An ensemble based technique, rather than enhancing an image with a single set of parameters, seeks to generate many enhanced versions in which certain image regions have a greater perceptual quality than the original input. The final enhanced result is created by smoothly combining the generated photos.

The authors of [25] employed LLSURE filters to produce images with less noise. Average fusion was used to achieve the final de-noised output. Wang et al. [26], Huang et al. [27] suggested ways to synthesis numerous exposure images in order to create an HDR image and accomplish HDR compression. A weighted combination result, on the other hand, may result in intensity discrepancy between neighbouring pixels if it is not properly modified. Multi-resolution blending approaches based on a Laplacian pyramid [28]–[30] can be used to avoid inconsistency by preserving image contrast and ensuring local intensity constancy. Despite the success of ensemble-based methods for HDR image compression, few ensemble-based methods for single image contrast enhancement, particularly for X-ray images, have been developed.

3. PROPOSED METHOD

A model for enhancing visual contrast has been proposed. An X-ray image may be made up of detachable and detail components, we reasoned. The term "removable components" refers to a portion of the body's tissue that can be removed. The detail components, on the other hand, are the important parts of the body, such as bones and organs. We attenuate the detachable components in an X-ray image to increase the dynamic range so that the detail components can be represented. To realize the concept, our image model is defined as:

$$In\,(x) = I\,(x)\,/Imax = D\,(x) + R\,(x) \qquad (1)$$

where In (x) is the normalisation image, I (x) is the input X-ray picture, Imax is the image's maximum value, D (x) is the detail component, and R (x) is the removable part. In addition, x is a spatial index, and the values of In (x), D (x), and R (x) are all between 0 and 1.

We created a constraint called "Local Contrast Maximization" to help us estimate T (x)(Tissue component). To stretch the local contrast, we can set R(x) = T (x), that is, 1 to get a very high contrast result. Stretching outcomes under R(x) = T (x) and R(x) = α

The map T (x) could be determined using the “Local Contrast Maximization” constraint by finding the best removable component map that maximises the sum of local contrast over the final enhanced image E.

$$T\,(x) \cong \min_{y \in L_x} I_n\,(y) \triangleq I_n^{min}\,(x)\,. \qquad (2)$$

In (2), Lx represents the local region around the pixel x, and y is a pixel inside Lx . Thus, the component map T (x) at pixel x can be estimated by finding the local minimum within a local region around x.

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We established an attenuation factor α, and defined R (x) = α .T (x) to manage the ratio for component removal in our method to estimate the attenuation component R(x). We can find R (x) to adequately enhance an X-ray image by estimating the maximum detachable tissue component map T (x) and regulating. Because the level of contrast enhancement is so closely related to the amount of tissue removed, it becomes the most important parameter in our parametric contrast adjustment model. Because the value of is invariant to pixel locations, we also treat as a global parameter in our parametric model.

The second controllable term in our model is λ (x). By introducing λ (x), our model can be adjusted to satisfy preferred image constraints. Unlikeα, λ (x) changes locally. In our system, we locally adjust the value of λ (x) at different locations in order to keep the brightness consistent. Below, we illustrate the determination T (x) and the calculation of the term λ (x)

However, if λ(x) is not correctly set, the result may be poor. As a result, we'll need to find a good λ (x) setting to maintain the image's local brightness consistent. After image enhancement, we require the maximum image value in a local area Lx to be maintained at the same level in our system. As a result, the brightness property can be preserved on a local level. As a result, we can define our brightness consistency requirement as follows:

$$E_n^{max}(x) \triangleq \max_{y \in L_x} E(y) = I_n^{max}(x) \triangleq \max_{y \in L_x} I_n(y). \quad (3)$$

Given a global attenuation ratio and the brightness of the scene, (3) restriction, the chosen parameter λ∗ (x) at

equation (4) can be used to calculate pixel x:

$$\lambda^*(x) = log\left[1 - \alpha I_n^{min}(x)\left(\frac{1}{I_n^{max}(x)} - 1\right)\right] / log\left(I_n^{max}(x)\right). \quad (4)$$

Because the interval of α is [0,1], equation (4) can be used to show that the interval of λ∗ is also [0,1]. The brightness of the original X-ray image is sometimes compressed worldwide, making brightness consistency problematic. To address the issue, we included a preprocessing step based on histogram equalisation in our processing phase to stretch the image histogram worldwide before applying the proposed primary technique.

A contrast enhancement function Ce (.) is applied to the detail component D (x) to produce the final enhanced X-ray Image E(x) .

E (x) = Ce (D (x)) = Ce (In (x) − R (x)) (5)

After eliminating R (x) from In (x), we should have enough room to improve D (x) by increasing its dynamic range. Image enhancement becomes conceivable if we can build the enhancement function Ce (.) to use the free dynamic range.

In our system, the designed enhancement function Ce (·) is

$$E(x) = Ce(D(x)) = \frac{I_n(x) - R(x)}{I_n^{max}(x)^{\lambda(x)} - R(x)}. \quad (6)$$

Here, I max n (x) = max y∈Lx I (y) is the local maximum of the local region, Lx ,around the image pixel x, and λ (x) is a controllable parameter.

We join the K enhanced images based on local image quality to get the final output image. We adapted the concept from Exposure Fusion for efficiency (EF) That is, given K enhanced images {Ei (x)}i=1 K , our system generates the combined image F (x) by

y F (x) = E F {Ei (x), Wi (x)}i=1K (7)

The Exposure Fusion algorithm is represented by EF(.) in (7). The weight map for the ith improved image is Wi (x). The position of a pixel is represented by the letter x. In addition, the total of weights for one pixel over K photographs must equal one.

3.1 Ensemble Enhancement Procedure.

Algorithm for preprocessing : Collect dataset of input image. Select 5 by 5 pixels from the input image. Apply adaptive histogramic equalization using CLAHE to improve intensity of image pixels. Normalize pixel matrix. Apply local minima for filtering out noise and local maxima for strengthen contrast both bright and dark regions. Attenuate component of local maximized image and enhance details. Do the same process for remaining pixels. Finally fuse the results.

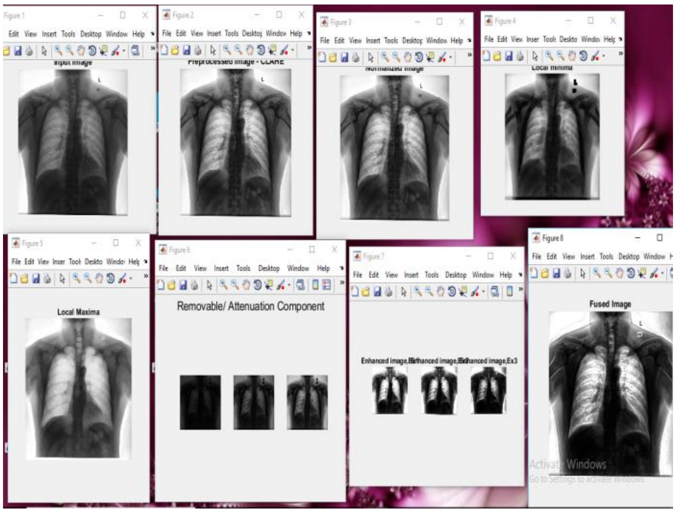

Fig -2: Preprocessing Output

4. CONCLUSION

The energy recorded in an X-ray image can show a human body's interior status. As a result, X-ray imaging has become a common method of health inspection. The poor contrast of an X-ray image, on the other hand, makes it difficult to spot small and aberrant details. A new enhancement technique based on component attenuation, contrast modification, and picture fusion is proposed in this work. We may adaptively increase the crucial information in both the bright and dark parts by attenuating the tissues over the image. A new parametric adjustment model was developed based on this approach. Users can simply improve visual contrast by altering the attenuation scale in the model.

REFERENCES

[1] Ching-Chun Huang , Member, IEEE, and Manh-Hung Nguyen , Member, IEEE, "X-Ray Enhancement Based on Component Attenuation, Contrast Adjustment, and Image Fusion" IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 28, NO. 1, JANUARY 2019

[2] P. Chaudhary, K. Shaw, and P. K. Mallick, "A survey on image enhancement techniques using aesthetic community," in Proc. Int. Conf. Intell. Comput. Appl., 2017, pp. 585–596.

[3] J.-Y. Kim, L.-S. Kim, and S.-H. Hwang, "An advanced contrast enhancement using partially overlapped sub-block histogram equalization," IEEE Trans. Circuits Syst. Video Technol., vol. 11, no. 4, pp. 475–484, Apr. 2001.

[4] S.-C. Huang, F.-C. Cheng, and Y.-S. Chiu, "Efficient contrast enhancement using adaptive gamma correction with weighting distribution," IEEE Trans. Image Process., vol. 22, no. 3, pp. 1032–1041, Mar. 2013.

[5] E. Land, "An alternative technique for the computation of the designator in the retinex theory of color vision," Proc. Nat. Acad. Sci. USA, vol. 83, no. 10, pp. 3078–3080, 1986.

[6] D. J. Jobson, Z.-U. Rahman, and G. A. Woodell, "Properties and performance of a center/surround retinex," IEEE Trans. Image Process., vol. 6, no. 3, pp. 451–462, Mar. 1997.

[7] A. B. Petro, C. Sbert, and J.-M. Morel, "Multiscale retinex," in Proc. Image Process. Line, 2014, pp. 71–88.

[8] Weizhen, L. Fei, and Z. Qinzhen, "The applications of improved retinex algorithm for X-ray medical image enhancement," in Proc. Int. Conf. Comput. Sci. Service Syst., Aug. 2012, pp. 1655–1658.

[9] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," IEEE Trans.

Pattern Anal. Mach. Intell., vol. 33, no. 12, pp. 2341–2353, Dec. 2011.

[10] C.-C. Huang, H.-N. Manh, and C.-Y. Tseng, "X-ray imaeg contrast enhancement based on tissue attenuation," in Proc. Int. Conf. Acoust., Speech Signal Process., May 2014, pp. 6602–6606.

[11] S. Paris, P. Kornprobst, J. Tumblin, and F. Durand, "Bilateral filtering: Theory and applications," Found. Trends Comput. Graph. Vis., vol. 4, no. 1, pp. 1–73, 2009.

[12] A. Gandhamal, S. Talbar, S. Gajre, A. F. M. Hani, and D. Kumar, "Local gray level S-curve transformation a generalized contrast enhancement technique for medical images," Comput. Biol. Med., vol. 83, pp. 120–133, Apr. 2017.

[13] A. Jabeen, M. M. Riaz, N. Iltaf, and A. Ghafoor, "Image contrast enhancement using weighted transformation function," IEEE Sensors J., vol. 16, no. 20, pp. 7534–7536, Oct. 2016.

[14] T. Celik, "Two-dimensional histogram equalization and contrast enhancement," Pattern Recognit., vol. 45, no. 10, pp. 3810–3824, Oct. 2012.

[15] T. Celik and T. Tjahjadi, "Contextual and variational contrast enhancement," IEEE Trans. Image Process., vol. 20, no. 12, pp. 3431–3441, Dec. 2011.

[16] C. Lee, C. Lee, and C.-S. Kim, "Contrast enhancement based on layered difference representation of 2D histograms," IEEE Trans. Image Process., vol. 22, no. 12, pp. 5372–5384, Dec. 2013

[17] T. Celik, "Spatial entropy-based global and local image contrast enhancement," IEEE Trans. Image Process., vol. 23, no. 12, pp. 5298–5308, Dec. 2014.

[18] T. Celik and L. Heng-Chao, "Residual spatial entropy-based image contrast enhancement and gradient-based relative contrast measurement," J. Mod. Opt., vol. 63, no. 16, pp. 1600–1617, 2016.

[19]]D. H. Choi, I. H. Jang, M. H. Kim, and N. C. Kim, "Color image enhancement using single-scale retinex based on an improved image formation model," in Proc. Eur. Conf. Signal Process., Aug. 2008, pp. 1–5.

[20] F. Durand and J. Dorsey, "Fast bilateral filtering for the display of highdynamic-range images," ACM Trans. Graph., vol. 21, no. 3, pp. 257–266, 2002.

[21] W. Wang, B. Li, J. Zheng, S. Xian, and J. Wang, "A fast multi-scale retinex algorithm for color image enhancement," in Proc. Int. Conf. Wavelet Anal. Pattern Recognit., vol. 1, Aug. 2008, pp. 80–85.

[22] J. Tang, X. Liu, and Q. Sun, "A direct image contrast enhancement algorithm in the wavelet domain for screening mammograms," IEEE J. Sel. Topics Signal Process., vol. 3, no. 1, pp. 74–80, Feb. 2009.

[23] X. Liu, J. Tang, S. Xiong, Z. Feng, and Z. Wang, "A multiscale contrast enhancement algorithm for breast cancer detection using Laplacian Pyramid," in Proc. Int. Conf. Inf. Automat., Jun. 2009, pp. 1167–1171.

[24] S. C. Nercessian, K. A. Panetta, and S. S. Agaian, "Non-linear direct multi-scale image enhancement based on the luminance and contrast masking characteristics of the human visual system," IEEE Trans. Image Process., vol. 22, no. 9, pp. 3549–3561, Sep. 2013.

[25] T. Qiu, A. Wang, N. Yu, and A. Song, "LLSURE: Local linear SUREbased edge-preserving image filtering," IEEE Trans. Image Process., vol. 22, no. 1, pp. 80–90, Jan. 2013.

[26] T.-H. Wang et al., "Pseudo-multiple-exposure-based tone fusion with local region adjustment," IEEE Trans. Multimedia, vol. 17, no. 4, pp. 470–484, Apr. 2015.

[27] C.-C. Huang, I. Leo, M.-X. Cai, and H. T. Vu, "HDR compression based on image matting Laplacian," in Proc. IEEE Int. Conf. Consum. Electron.-Taiwan (ICCE-TW), May 2016, pp. 301–303.

[28] T. Mertens, J. Kautz, and F. Van Reeth, "Exposure fusion: A simple and practical alternative to high dynamic range photography," Comput. Graph. Forum, vol. 28, no. 1, pp. 161–171, 2009.

[29] W. Zhang and W.-K. Cham, "Gradient-directed multi exposure composition," IEEE Trans. Image Process., vol. 21, no. 4, pp. 2318–2323, Apr. 2012.

[30] P. J. Burt and E. H. Adelson, "The Laplacian pyramid as a compact image code," IEEE Trans. Commun., vol. COM-31, no. 4, pp. 532–540, Apr. 1983.