X-RAY ENHANCEMENT BASED ON COMPONENT ATTENUATION, CONTRAST ADJUSTMENT, AND IMAGE FUSION

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Abstract *Inspecting X-ray images is an essential aspect of medical diagnosis. However, due to an X-ray's low contrast and low dynamic range, important aspects such as organs, bones, and nodules become difficult to identify. Hence, contrast adjustment is critical, especially in view of its ability to enhance the details in both bright and dark regions. For X-ray image enhancement, we therefore propose a new concept based on component attenuation. Notably, we assumed an X-ray image could be decomposed into tissue components and important details. Since tissues may not be the major primary of an X-ray, we proposed enhancing the visual contrast by adaptive tissue attenuation and dynamic range stretching. Via component decomposition and tissue attenuation, a parametric adjustment model was deduced to generate many enhanced images at once. Finally, an ensemble framework was proposed for fusing these enhanced images and producing a highcontrast output in both bright and dark regions. We have used measurement metrics to evaluate our system and achieved promising scores in each. An online testing system was also built for subjective evaluation. Moreover, we applied our system to an X-ray dataset provided by the Japanese Society of Radiological Technology to help with nodule detection. The experimental results of which demonstrated the effectiveness of our method.*

Keywords—*X-ray Image Enhancement; Component Attenuation; Ensemble Framework; Parametric Contrast Adjustment Mode*

1. INTRODUCTION

Inspecting X-ray images is an important step for medical diagnosis. However, low contrast and low dynamic range of an X-ray image make these body parts embedded in the bright or dark regions difficult to identify. The bright regions of an Xray image are of interest because many important organs and bones are located here. In contrast, tiny but significant details, such as nodules usually appear in the dark regions. To identify organs and nodules simultaneously, a higher dynamic range is needed to clearly characterize both the bright and dark regions. Without enhancement, it is challenging to show details in a standard and low-dynamic-range (LDR) X-ray image.

Examples of X-ray images offered by a local hospital are shown in Fig. 1. The low contrast and the low dynamic range of these images make it hard to see the details and to make a correct diagnosis. To help with this, we propose an ensemble framework, which consists of tissue attenuation, contrast adjustment, and image fusion, for X-ray image enhancement. By increasing the contrast in bright regions and dark regions, our system aims to clearly present the details in LDR X-ray images apparently.

As we will discuss in CHAPTER II, many previous methods have been proposed to enhance an image's contrast, such as global tone mapping [1], local adaptive tone mapping [2-4], Retinex-based methods [5-8], and transform-based methods [10]. These works are closely related to tone mapping that reduces the dynamic range of an HDR image and produces a contrast-enhanced LDR image. Similarly, our proposed method also relies on the concept of

tone mapping to increase the local contrast. However, compared with the previous works, there are several differences in the design methodology. Below, we summarize the differences and contributions of our method.

Two typical X-ray images in our testing dataset

2. LITERATURE REVIEWS

Longkumer et al. (2014) gives a comparison of the various histogram equalization techniques and gives their merits and demerits. They include Adaptive Histogram Equalization (AHE), Classical Histogram Equalization (CHE), Recursive Mean Separate Histogram Equalization (RMSHE), Brightness Preserving Bi- Histogram Equalization (BPBHE) and Background Brightness Preserving Histogram Equalization (BBPHE). On comparing them it was discovered that BBPHE provides a better and scalable brightness preservation for images with poor contrast and avoids unwanted noise.

Rajesh et al. (2011) did a comparative analysis of the different enhancement techniques frequently employed in industries. They investigated the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique, the Dynamic Histogram Equalization (DHE) technique and the Dualistic Sub-Image Histogram Equalization (DSIHE) method. The comparison was by using both subjective and objective criterion. The subjective factor used was the visual quality while the objective factors used were Peak Signal to Noise Ratio (PSNR) and Normalized Correlation (NC). The CLAHE procedure was found to give better output in terms of PSNR and DSIHE gives the best results when considering the absolute mean brightness error.

Jin et al., (2011) developed an industrial image de-noising and enhancement system by using wavelets and histograms. Since most of the X-ray image pixels are found on the low frequency spectrum and very few pixels, if any, are on the high frequency range, their techniques called Contrast Limited Adaptive Histogram Equalization (CLAHE) handled low contrast and poor details effectively. They found out that the results of enhanced images had more information details and became clearer.

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:

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

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 maximizes the sum of local contrast over the final enhanced image

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

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.

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 equalization 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

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

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

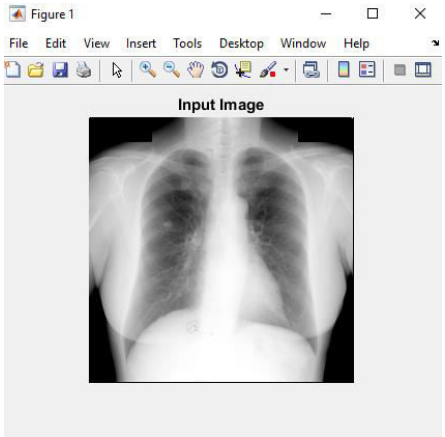
y F (x) = E F {Ei (x), Wi (x)}i=1K (7)

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.

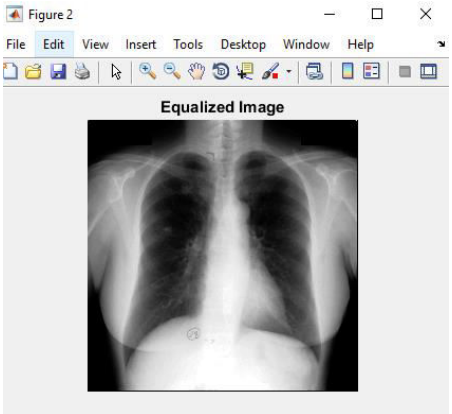
4. RESULTS AND ANALYSIS

Example Image 1 Results

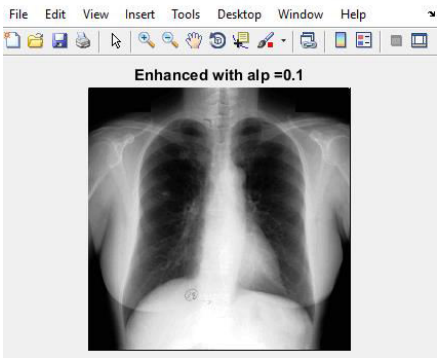
Input image 1



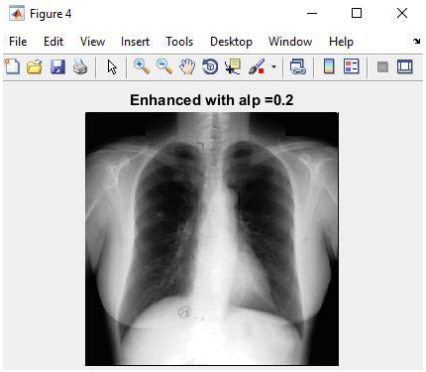
Input image



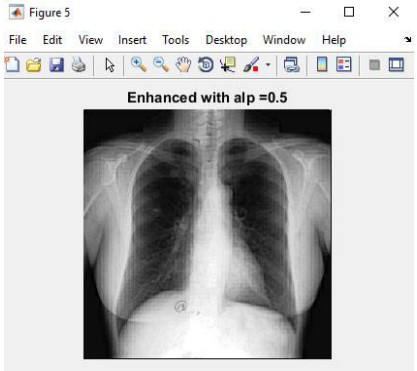
Equalized image



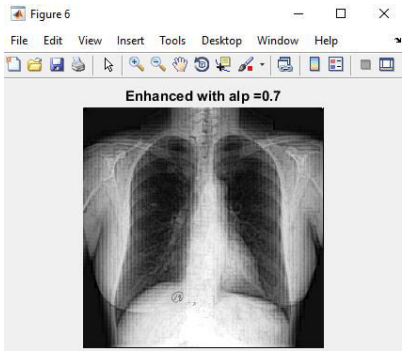
Enhanced image with alp=0.1



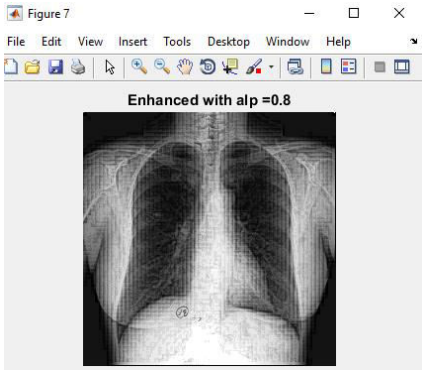
Enhanced image with alp=0.2



Enhanced image with alp=0.5



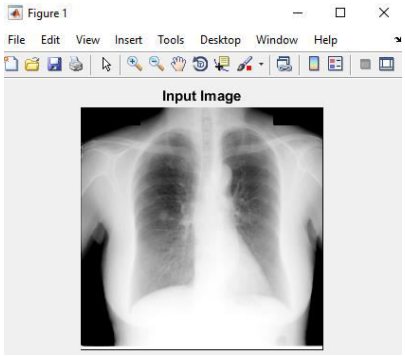
Enhanced image with alp=0.7



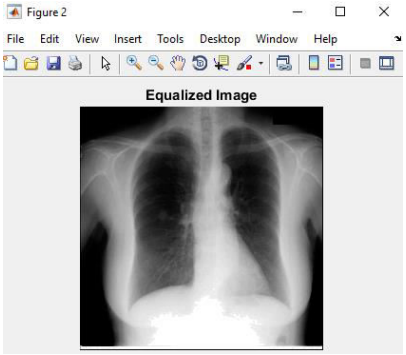
Enhanced image with alp=0.8

Example Image 2 Results

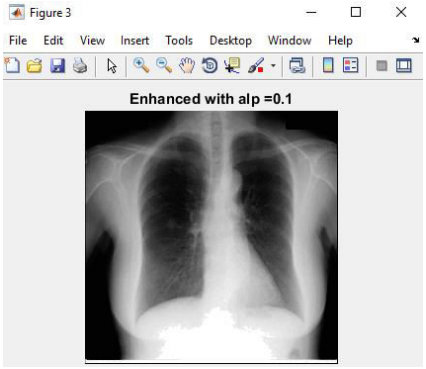
Input image 2



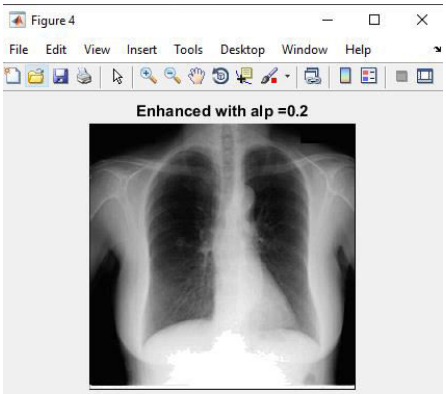
Input image



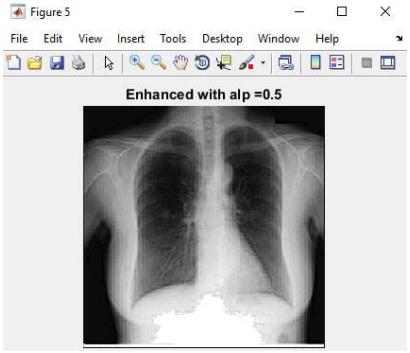
Equalized image



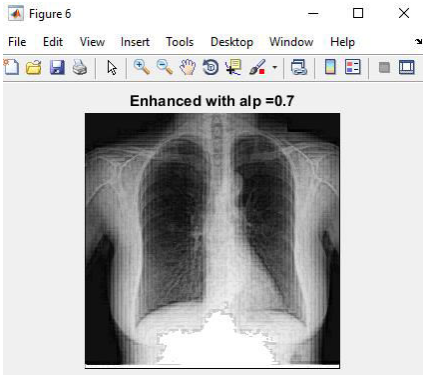
Enhanced image with alp=0.1



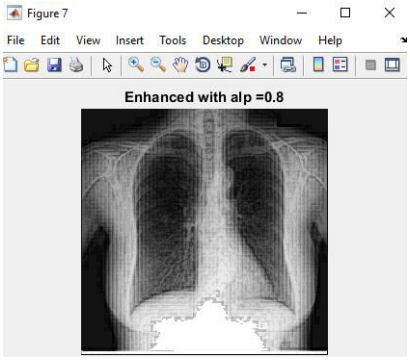
Enhanced image with alp=0.2



Enhanced image with alp=0.5



Enhanced image with alp=0.7



Enhanced image with alp=0.8

5. CONCLUSIONS

1. The energy recorded in an X-ray image is able to reveal the internal condition of a human body. Thus, X-ray imaging has become a standard tool for health inspection. However, the low contrast property of an X-ray image makes it hard to recognize tiny and abnormal details.
2. In this study, a new enhancement system based on component attenuation, contrast adjustment, and image fusion was proposed. By attenuating the tissues over the image, we can enhance the essential details in both the bright and dark regions adaptively. Established in this concept, a

novel parametric adjustment model was formulated.

3. The model enables users to easily enhance image contrast by adjusting the attenuation scale. To locally enhance the contrast, an ensemble strategy was also proposed to fuse many enhanced images and generate the final output by maximizing the visual contrast.
4. We have used four measurement metrics and two datasets to evaluate our system. The results demonstrated the effectiveness of our method to enhance organs, bone structure, and some small but significant details, such as tiny nodules in low contrast X-ray images.
5. Moreover, an online testing system was also built for subjective evaluation. It showed that our system can help doctors with disease inspection.

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