

X-RAY IMAEG CONTRAST ENHANCEMENT BASED ON TISSUE ATTENUATION

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ABSTRACT

X-ray imaging is an efficient tool for health inspection. The energy of received X-ray could reveal the density inside human body and be represented in an X-ray image. In general, the bright regions of an X-ray image are of interest since most important matters compactly locating in those regions. However, the low contrast property of the bright regions makes inspectors hard to tell the details. Hence, contrast enhancement of X-ray images especially in the bright regions becomes critical. In the paper, unlike previous algorithms which work well in the dark regions, we thus proposed a tissue attenuation method to enhance the bright regions. We assume the X-ray intensity is composed of tissues and other important details. By locally attenuating the ratios of tissues over the image, we could adaptively enhance the important details especially in the bright regions. To adjust the ratios, a two-step procedure was proposed. First, the tissue component was separated from a given image based on local contrast maximization. Second, an attenuation adjustment was performed to control the ratio of removable tissues in order to correctly enhance contrast. Experimental results also demonstrate the effectiveness of our method.

Index Terms—Tissue Attenuation, X-ray Imaging, Contrast Enhancement, Contrast Maximization.

1. INTRODUCTION

In a typical physical process, an X-ray image is formed by interaction of an energy source and matters. When an energy beam penetrates a human body, matters such as bone, muscle, or water absorb partial energy of the beam. While an object is physically different from its surroundings, it will absorb more or less energy against the surroundings and present different intensities. If the mass per unit area of the matters is high, the corresponding region would be bright. In contrast, less dense areas would be presented by dark regions in the content. Those intensities are recorded by a film or a receptor, and an X-ray image is formed.

In general, the bright regions of an X-ray image are of interest since most important matters compactly locating in

those regions. However, those regions usually present low contrast as shown in Fig. 1. Without contrast enhancement, it would be inconvenient to inspect the details. Thus, in this paper, we focus on X-ray contrast enhancement especially on the bright regions.

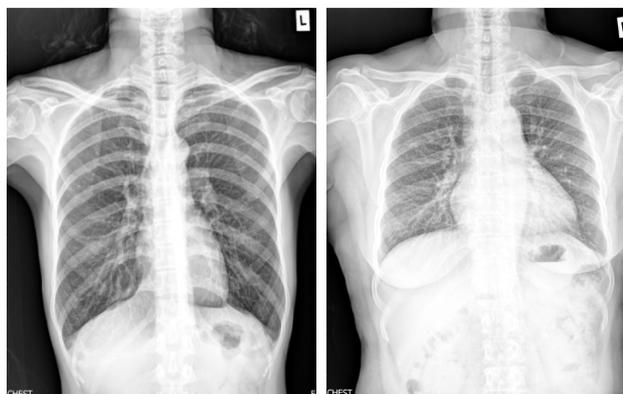


Fig. 1. Two X-ray images whose bright regions present low contrast.

To enhance the visual quality of images with low contrast, many approaches have been presented such as global tone mapping methods [1], adaptive tone mapping methods [2-4], and retinex-based methods [5-9]. The global tone mapping methods pursue a mapping function to transfer input intensity values into new values while enlarging the global contrast, yet a typical drawback is that image details may be sacrificed. In contrast, adaptive tone mapping methods pursue spatially varying transfer functions to enhance detailed contrast [2-4]. For the local adjustment, maintaining the spatial consistency would be a crucial issue. The retinex theorem [5] suggests computational methods of human contrast sensitivity function to suppress the bias of illumination to enhance detailed contrast [6-9]. For low illumination or dark regions, the retinex-based methods can provide vivid enhanced results. Unfortunately, when dealing with bright regions, based on the retinex theorem, the computed contrast sensitivity is typically weak; thus, the degree of enhancement is limited.

Unlike the conventional approaches mentioned above, we presented a different viewpoint to enhance an X-ray image, especially the bright regions. We found the human body is casted by different amounts of tissues in different

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regions. Thus, the proposed enhancement technique was based on removing certain of tissues which causes the acquired regions to be overly bright for detail visualization. By taking a physical assumption that the intensity value of the acquired image is the composition of tissues and other important details, we proposed to decompose an image into a removable tissue component and an enhanced detail component. The extraction of the tissue component was posed as a contrast maximization problem. Since tissues may not be the major focus of X-ray imaging, the visual contrast of the detail component could be greatly enhanced by tissue attenuation and dynamic range stretching. With different attenuation factors, our system could provide enhanced results with flexible degree of visualization.

The rest of this paper is organized as follow. We detail the proposed method in section 2 and summarize our system flow in section 3. Experimental results and discussion are given in section 3. In section 4, we conclude this paper.

2. THE PROPOSED METHOD

In this section, we detail the proposed method. In section 2.1, we introduce our image model and the tissue attenuation idea, which we used to enhance image contrast. In section 2.2, we illustrate the way to estimate the tissue component over an X-ray image based on local contrast maximization. Finally, we propose a tissue attenuation mechanism to adjust tissue ratios and enhance X-ray images.

2.1 Image Contrast Enhancement Model

Here, an X-ray image was modeled as the composition of a removable tissue component and an enhanced detail component. To enhance an X-ray image, we attempted to reduce the amount of tissues and give a wider dynamic range to represent the detail component. To realize the concept, we defined the removable amount of tissues as $R(x)$ and the enhanced details as $E(x)$. Here, x is a spatial index, and both $R(x)$ and $E(x)$ range between 0 and 1. Furthermore, we assumed that a normalized X-ray image $I_n(x)$ could be represented by

$$I_n(x) = I(x)/I_{max} = E(x) \cdot (1 - R(x)) + R(x), \quad (1)$$

where $I(x)$ is the original image and I_{max} is the maximum image intensity over the image. If $R(x)$ could be reasonably determined, the enhanced details $E(x)$ could be calculated by

$$E(x) = (I_n(x) - R(x)) / (1 - R(x)). \quad (2)$$

Since $I_n(x) \geq R(x)$ and both $I_n(x)$ and $R(x)$ range between 0 and 1, the function of equation (2), as shown in Fig 2., is to linearly stretch the dynamic range. Therefore, by locally adjusting $R(x)$, we could obtain the enhanced details $E(x)$. Intuitively, if the tissue component over the image is $T(x)$, we may set $R(x)=T(x)$ in order to remove all tissues and most stretch the image contrast to get a highly enhanced result $E_{high}(x)$ as shown in Fig. 2(a). However, tissues could be water, muscle, or fat; some of the tissues are also parts of organs and could not be all removed. If removing all tissues to enhance contrast, we may also lose some details of

organs. To better select the removable tissue component $R(x)$, we introduced an attenuation factor $A(x)$ to control the removable ratio of tissues. By setting $R(x) = A(x) \cdot T(x)$, we could get a reasonably result $E_{result}(x)$ as shown in Fig. 2(b). We named the process as tissue attenuation, and aimed to determine $A(x)$ and $T(x)$ so as to enhance an image based on equation (2). Next, we would introduce the details.

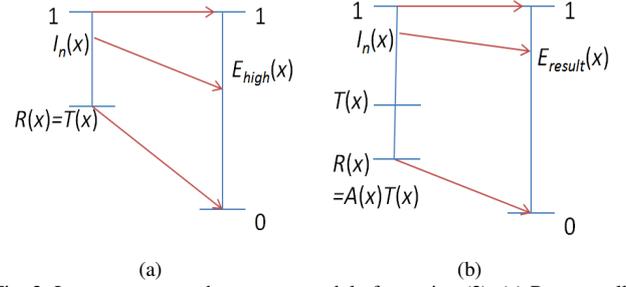


Fig. 2. Image contrast enhancement model of equation (2). (a) Remove all tissues and (b) properly attenuate the amount of tissues.

2.2 Estimation of the Tissue Component

In this section, we discuss the determination of the tissue component $T(x)$. However, without extra information, this is an ill-posed problem. Here, we adopted a constraint based on contrast maximization. In particular, if we set $R(x)=T(x)$ to remove all tissues and stretch the local contrast, we will achieve an high contrast image $E_{high}(x)$. Since $E_{high}(x)$ is free of tissues, we expect the local contrast of $E_{high}(x)$ will be maximized. Thus, by finding the $R(x)$ that maximizes the local contrast of $E(x)$, we may determine $T(x)$. Here, we defined the local contrast (LC_x) of $E(x)$ at pixel x as

$$LC_x = E(x) - \min_{y \in W_x} E(y), \quad (3)$$

where W_x is a n -by- n window around pixel x , and y is a pixel inside W_x . Note that we used a 7×7 window in our system. The tissue component $T(x)$ is then estimated by the following optimization problem

$$T(x) = R^{LC}(x) = \operatorname{argmax}_{R(x)} (E(x) - \min_{y \in W_x} E(y)). \quad (4)$$

To maximize the local contrast LC_x , the optimal $R^{LC}(x)$ should maximize the term “ $E(x)$ ” and minimize the term “ $\min_{y \in W_x} E(y)$ ” simultaneously. According to equation (2), to maximize the term “ $E(x)$ ”, $R^{LC}(x)$ should be as small as possible to make the difference of $I_n(x)$ and $R(x)$ as large as possible. On the other hand, to minimize the term “ $\min_{y \in W_x} E(y)$ ”, $R^{LC}(x)$ at pixel x should be set to be one of the intensity values within the set $\{I_n(y)\}_{y \in W_x}$ to make $\min_{y \in W_x} E(y)$ become zero. Combining the two constraints, the optimal solution of equation (4) is

$$T(x) = R^{LC}(x) = \min_{y \in W_x} I_n(y). \quad (5)$$

Thus, the tissue component $T(x)$ could be determined by finding the local minimum within a small region. To explain this result, we could assume the casted tissue within a small region is constant. Moreover, in an X-ray image, if an image pixel is composed of not only the casted tissue but also other matters, its intensity would be higher than pixels only casted the tissue. Hence, the local minimum of $I_n(y)$ can be a

reasonable estimation of $T(x)$. Also, the minimum intensity in a bright region is usually high; this leads to a higher $T(x)$ and a wider dynamic range to enhance the bright regions.

2.3 Tissue Attenuation

Although using $R^{LC}(x)$ could achieve contrast maximization, the result image $E_{high}(x)$ may be over-enhanced. As shown in Fig. 3(a), because of removing all the tissues, some important details are also lost. Hence, we proposed tissue attenuation rather than tissue removal to overcome the problem. By well controlling the attenuation factor $A(x)$, we attempted to enhance bright regions and preserve the image details while locally optimizing the image contrast. To fulfill the goal, we divided $A(x)$ into two terms: a gamma adjustment term $G(x)$ and an energy preserving term $P(x)$. That is

$$A(x) = G(x) \cdot P(x). \quad (6)$$

Since contrast enhancement in bright regions is critical for the X-ray inspection, we defined the gamma adjustment term $G(x)$ by equation (7) to enhance the bright regions.

$$G(x) = MI_n(x)^\gamma. \quad (7)$$

In (7), $MI_n(x) = Mean_{y \in W_x} I_n(y)$ is the local mean of $I_n(x)$ over W_x and $\gamma = 0.5$. For bright regions, $MI_n(x)$ is high, $G(x)$ would be close to 1, and more tissues could be removed for contrast enhancement.

On the other hand, to preserve the original image details, we used the term $P(x)$. We hope the local energy difference of the original and enhanced images to be small. Therefore, we measured the local mean of the original image $I_n(x)$ and the high contrast image $E_{high}(x)$. If their difference is large, it implicitly implies the region is over enhanced; fewer tissues should be removed, and $P(x)$ should be small. Based on the concept, we defined $P(x)$ as

$$P(x) = \exp^{-\alpha(MI_n(x) - ME_{high}(x))^2}, \quad (8)$$

where $ME_{high}(x) = Mean_{y \in W_x} E_{high}(y)$ is the local mean of $E_{high}(x)$ and α is a parameter controlling the effect of $P(x)$. We set $\alpha = 0.1$ in our implementation. Once $G(x)$ and $P(x)$ are determined, the final enhanced image $E_{result}(x)$ can be achieved. Fig. 3(b) is an example.

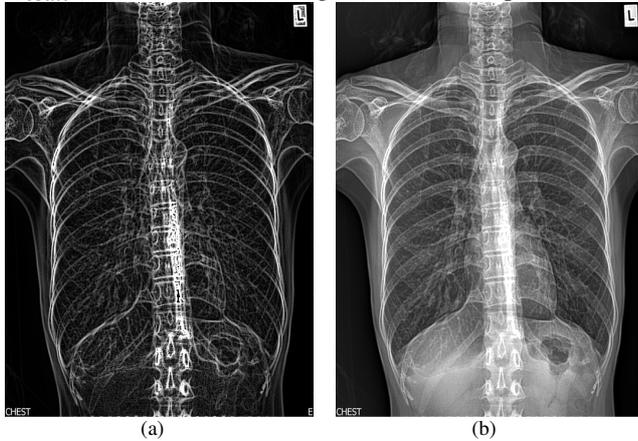


Fig. 3. Contrast enhancement based on Tissue Attenuation. (a) The over-enhanced image $E_{high}(x)$ and (b) the properly enhanced image $E_{result}(x)$.

3. SYSTEM FLOW

In Fig. 4, we show the system flow to summary our method. First, a normalized image $I_n(x)$ is calculated. By finding the local minimum of $I_n(x)$, we get tissue component $T(x)$. Next, we set $R(x)=T(x)$ and achieve an over-enhanced result $E_{high}(x)$ by equation (2). To calculate the attenuation factor $A(x)$, we input $I_n(x)$ and $E_{high}(x)$ to the ‘‘tissue attenuation’’ step. Finally, by setting $R(x) = A(x) \cdot T(x)$ and enhancing image contrast by equation (2), we achieve the final result.

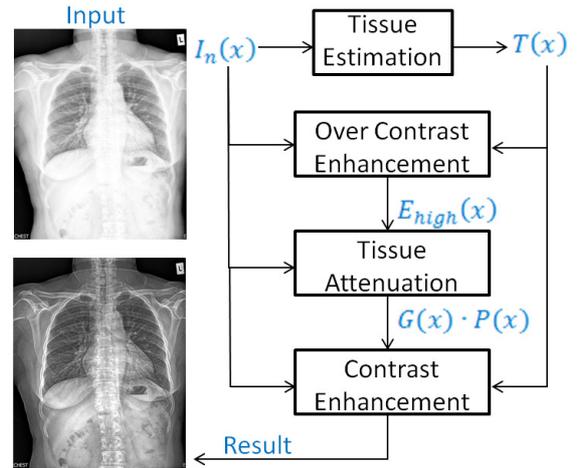


Fig. 4. The system flow of the proposed method.

4. EXPERIMENTAL RESULTS

In order to evaluate the effectiveness and robustness of the proposed method, we tested our system by using many X-ray medical images from a local hospital. Some testing images and enhanced results are shown in Fig. 5. As shown in Fig. 5, the original images are over bright, low contrast, and hard to see the details. The proposed tissue attenuation method could enhance the local contrast and present the details well for further inspection.

In Fig. 6(c) and 6(d), we compare our approach with two global contrast adjustment methods: histogram equalization and Gamma adjustment. Without considering the local property, the visualization of the local details is not well improved. We also compare our results with the algorithms proposed in [4] and [7] as shown in Fig. 6(e) and 6(f). The two algorithms were proposed to enhance the local contrast. However, when dealing with X-ray images, the computed contrast sensitivity is weak in the bright regions. Thus the degree of enhancement is limited. In contrast, our approach could improve the image contrast especially for the bright regions.

To evaluate the effectiveness of the proposed method quantitatively, we use the metrics: Measure of Enhancement (EME) [10]. The EME could be calculated by equation (9).

$$EME = \frac{1}{k_1 k_2} \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} 20 \cdot \ln \frac{I_{i,j}^{max}}{I_{i,j}^{min}}, \quad (9)$$

where the image is divided into k_1 -by- k_2 patches and $I_{i,j}^{max}$ and $I_{i,j}^{min}$ are the maximum and minimum intensities in the corresponding patch. For comparison, the EME values of our method and some previous methods are showed in Table I, where our method has better performance in EME.

Finally, our algorithm is implemented using Matlab on an Intel Core i5 3.0 GHz CPU with 4GB of memory. It takes about 0.2 seconds to process a standard chest X-ray image.

TABLE I. The Comparison of EME Values.

Method	EME	Method	EME
Original image	5.5928	Proposed method	10.557
Histogram equalization	8.3881	Gamma Mapping	7.3836
Schettini et al.'s [4] method	9.2445	Weizhen et al.'s [7] method	3.9790

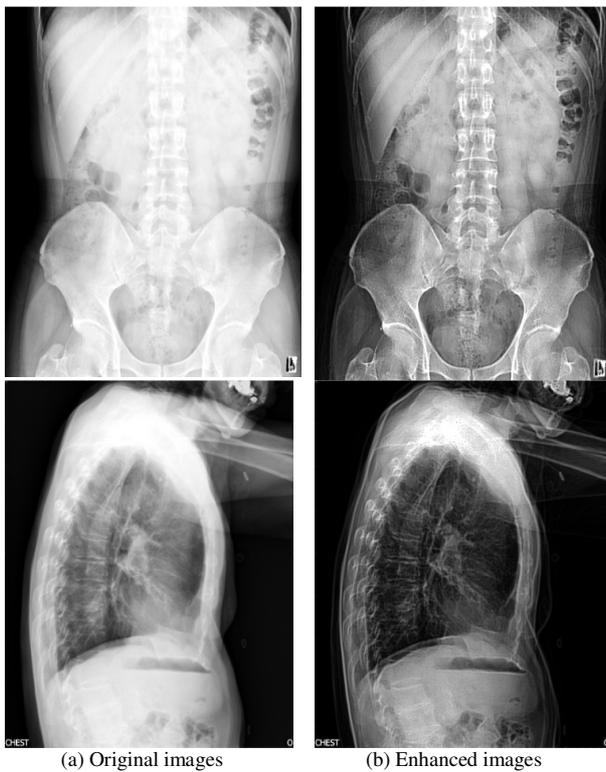


Fig. 5. X-ray image enhancement.

5. CONCLUSIONS

In this paper, an X-ray contrast enhancement method based on tissue attenuation is proposed. We found the human body is casted by tissues. By estimating the amount of the tissue component and locally adjusting the ratios of remaining tissues, our system can achieve contrast enhancement in an efficient manner especially for bright regions. Experimental results have demonstrated our algorithm could effectively present X-ray details for inspection. The computational cost of our method is also affordable for a real-time application. In the future, we plan to design an optimization strategy to determine the optimal parameters for tissue attenuation.

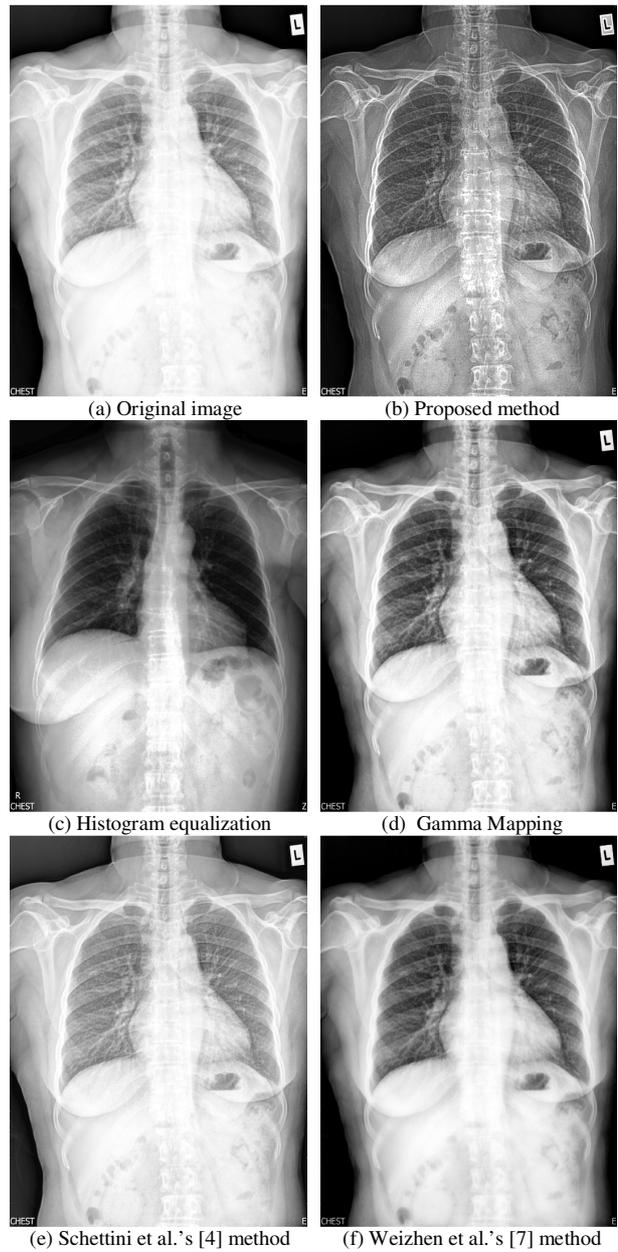


Fig. 6. The result comparison based on different methods.

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