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Chest radiograph image enhancement with wavelet decomposition and morphological operations

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Abstract

Medical image processing algorithms significantly affect the precision of disease diagnostic process. This makes it crucial to improve the quality of a medical image with the goal to enhance perceivability of the points of interest in order to obtain accurate diagnosis of a patient. Despite the reliance of various medical diagnostics on X-rays, they are usually plagued by dark and low contrast properties. Sought-after details in X-rays can only be accessed by means of digital image processing techniques, despite the fact that these techniques are far from being perfect. In this paper, we implement a wavelet decomposition and reconstruction technique to enhance radiograph properties, using a series of morphological erosion and dilation to improve the visual quality of the chest radiographs for the detection of cancer nodules.

Keywords: *chest radiograph, image enhancement, mathematical morphology, wavelet decomposition*

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1. Introduction

A chest radiograph provides a great measure of medical information about a patient's condition pertaining to such diseases as lung cancer and chest infections. However, images produced by X-Rays, are filled with noise due to interferences from capturing devices and anatomical structures [1]. The prime inspiration in the vast majority of the computer algorithms for helping radiologists in examining chest radiograph images, is the clinical significance of chest radiograph [2]. Locating cancer nodules in chest radiographs helps to detect early signs of lung cancer. However, anatomical structures usually constitute unwanted artifacts in captured X-ray images. Due to the size and density, nodules are usually difficult to detect in a chest radiograph [3, 4]. Image processing algorithms are designed to improve the accuracy of the diagnostic procedure [5], especially, in applications in Computer Assisted Diagnosis (CAD) systems [6]. Despite this, image processing algorithms are not perfect.

Some of the most utilized algorithms relied upon to enhance the quality of chest radiographs include parameterized logarithmic image filtering method based on Laplacian of Gaussian (LoG) [7], the Hessian-LoG filter [8], and the mean and median filtering for noise removal [9]. These filters are only appropriate for certain types of noises and are inadequate for enhancing medical images such as a chest radiograph. Recently, a total variation approach has been used to enhance the local contrast in chest radiographs leading to significant improvement. [4]. Another common technique used in feature-based enhancement classification is the classic unsharp masking method. The Fully Convolutional Neural Networks (FCNN) is utilized to improve the contrast of delicate lung structures in chest radiographs [10-14]. These methods improve the image contrast but not only fall short in detecting lung cancer nodules, but in addition, lead to unacceptable number of false positives and false negatives.

We implement a discrete wavelet transform combined with morphological tools to enhance chest radiographs. This leads to an efficient method of denoising and enhancement

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of x-ray images, that outperforms wavelet transforms based techniques [15]. Our algorithm is implemented in Python, leading to consistency in the quality of the results obtained. The strategy strikingly enhances points of interest in chest radiographs while preserving the details of delicate chest tissue, so radiologists may have a more exact clarification of diagnosis [16].

Due to its multiresolution capabilities, the wavelet transform has become a powerful image processing tool [17, 18]. Wavelets have a localizing property and a characteristic of denoising in a time-scale domain and hence making available local details of an image with minimal loss of detail. Wavelet based image enhancement techniques such as histogram equalization and gamma adjustments when applied to chest radiographs, however, lead to loss of vital image details [19]. Existing methods such as kernel and spline estimators, tend not to resolve local structures well, and spatial techniques such as the median and mean filters have the demerit of blurring the edges of an image in an attempt to smoothen the image to remove noise [17]. This is catastrophic in applications to medical imaging.

In order to eliminate the problems listed above, we introduce a technique to remove anatomical noise whiles preserving details. Firstly, we use the dyadic wavelet transform that has the capability to locally decompose an image to remove the unwanted details and then reconstruct the image using the derived wavelet coefficients. We then apply the morphological erosion and dilation for several iterations to enhance the cancer nodules and realize a better appearance, using a small and ellipsoidal structuring element.

2. Morphological Erosion and Dilation

Mathematical morphology is a technique for extracting and analysing the parts of an image that are of interest to the researcher. It is based on set theoretical axioms and is derived from the basic Minkowski set operations of addition and subtraction. In this formulation, images are considered as functions mapped from the euclidean space M into $\mathbb{R} \cup \{\infty, -\infty\}$. Structuring functions which are known as structuring elements are functions of the same form as the images. Given two image sets A and B , the minkowski addition is defined by $A \oplus B = \underset{\beta \in B}{\cup} (A + \beta)$ and the subtraction is defined by $A \ominus B = \underset{\beta \in B}{\cap} (A + \beta)$. The set A represents the image data and the set B is the structuring element. The structuring element plays a similar role that convolution kernels play in linear image filtering. The basic morphological operators, dilation and erosion are based on these two operations. Given an image function $f(x)$ and a structuring function $s(x)$, the grayscale dilation of f by s is defined as

$$D(f, s) = (f \oplus s)(x) = \underset{y \in M}{sup} \, [(f(y) + s(x - y)]$$

and erosion of f by s is defined by

$$E(f, s) = (f \ominus s)(x) = \underset{y \in M}{inf} \, [(f(y) - s(y - x)]$$

A flat structuring function is defined as

$$s(x) = \begin{cases} 0, & x \in S \\ -\infty & otherwise \end{cases}$$

$S \subseteq M$, is the structuring function support. With this kind of structuring element, only true pixels are counted in the morphological computation. This thus simplifies the definitions of dilation and erosion to

$$D(f, s) = (f \oplus s)(x) = \underset{z \in S^s}{sup} (f(x + z)$$

and

$$E(f, s) = (f \ominus s)(x) = \underset{z \in S}{inf} (f(x + z)$$

respectively, where S^s denotes the symmetric structuring function support. Applying dilation operation to an object causes it to grow in size by the structuring element, whereas erosion causes the object to shrink [20, 21, 22, 23].

Cancer nodules have high intensity values than the adjacent usually bright anatomical structures [24]. As such, we erode the image first to get rid of all noisy details and then we dilate the result using an elliptical structuring element. This significantly improves the visibility of nodules to even the naked eye in X-Rays.

3. Results

We implemented our technique on a database of a set of 247 chest X-ray images from a standard Public Database; the Japanese Society of Radiological Technology. This database is endowed with different cases which makes it the appropriate choice. These images were collected over a three year period from 14 medical institutions and are made up of anterior and posterior films of measure 14×14 inches. There are 154 images which have lung nodules, out of which 100 are malignant and 54 are benign. 93 of the images are without lung nodules. Nodules are confirmed by CT and their locations are confirmed by three radiologists [25]. We implemented our technique on 100 images with nodules and 60 images with no nodules. Our result showed visible presence of nodules in 100% of the images with nodules, eliminating completely the occurence of false positives and false negatives. Samples of our results are displayed in the Figures 1. Figure 1 is a wavelet decomposition and reconstruction compared with the original images.

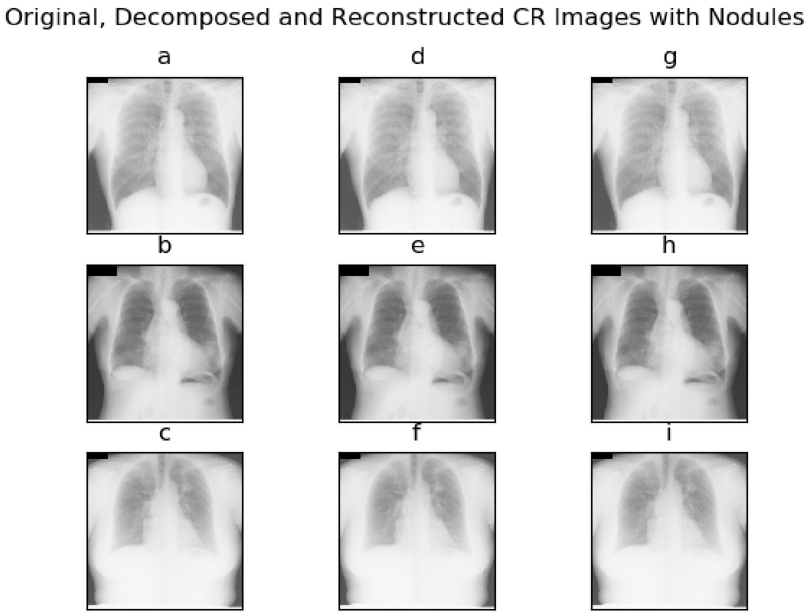

Figure 1. (a-c) are the original chest images with nodules, (d-f) are the wavelet decomposition of images in (a-c), (g-i) are the reconstructed images from the decomposed images (d-f)

Figure 2 forms part of the sample used in Figure 1. It shows the wavelet decomposition and reconstruction compared with the original images. Figure 3 shows a wavelet decomposition and reconstruction compared with the original images. Figure 4 completes the set of images that compare wavelet decomposition and reconstruction with the original images. Morphological erosion and dilation are successively applied to the sample of chest radiograph images. Part of the results are shown in Figure 5. Figure 6 is the second sample of images that have been processed with morphological operations. The third set of the results of processing the sample of images with morphological erosion and dilation is displayed in Figure 7. The final set of the results of processing the sample of images with morphological erosion and dilation is displayed in Figure 8.

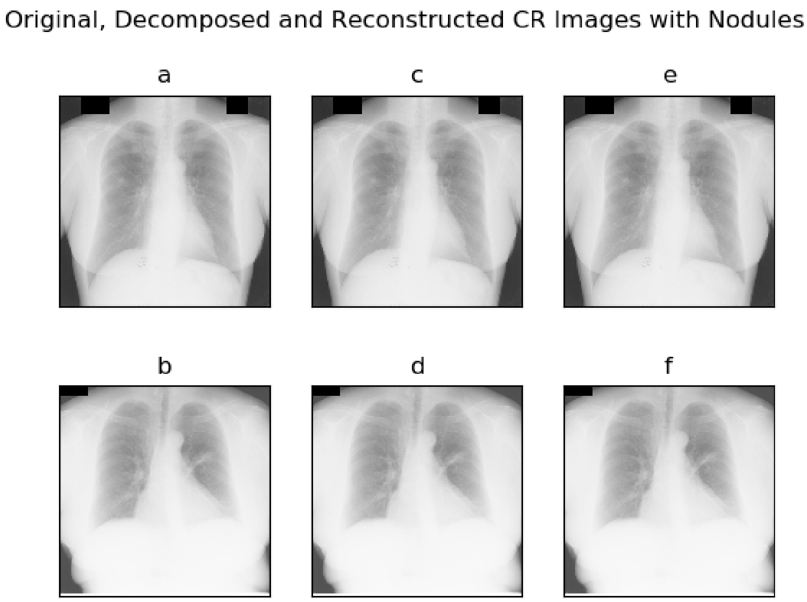

Figure 2. This is part of the sample of images shown in Figure 1. (a-b) are the original chest images with nodules, (c-d) are the wavelet decomposition of images in (a-b), (e-f) are the reconstructed images from the decomposed images (c-d)

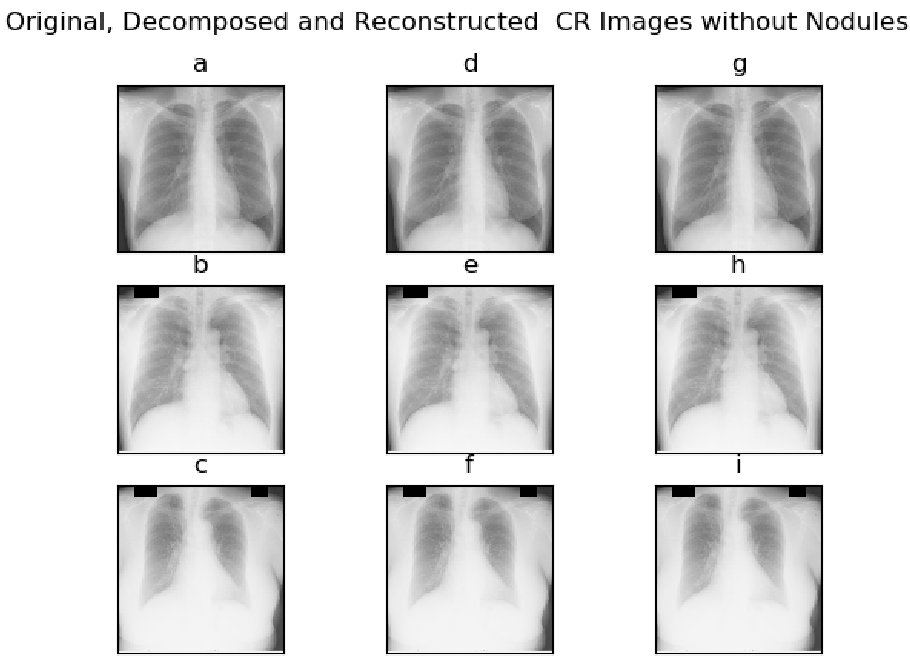

Figure 3. (a-c) are the original chest images without nodules, (d-f) are the wavelet decomposition of images in (a-c), (g-i) are the reconstructed images from the decomposed images (d-f)

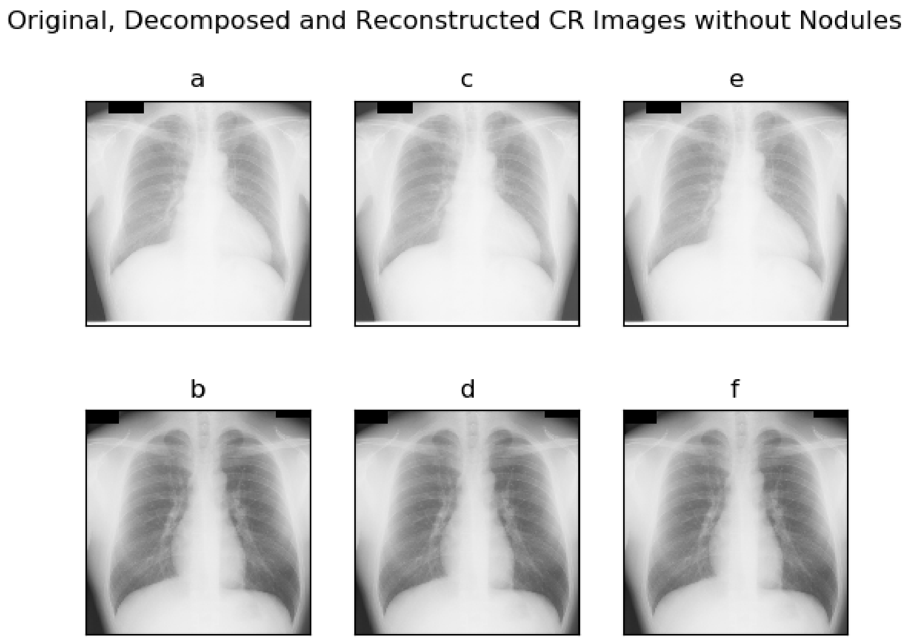

Figure 4. This is part of the sample of images in Figure 3 which shows (a-b) are the original chest images without nodules, (c-d) are the wavelet decomposition of images in (a-b), (e-f) are the reconstructed images from the decomposed images (c-d)

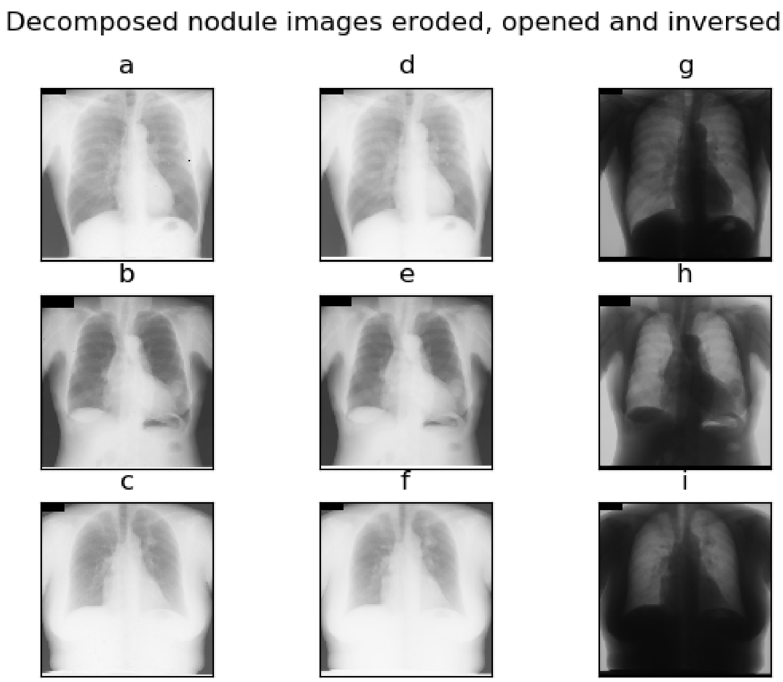

Figure 5. (a-c) are the result of applying morphological erosion to reconstructed chest images with nodules, (d-f) show dilation of the eroded images in (a-c) (Opening), (g-i) show inverted images of the images in (d-f)

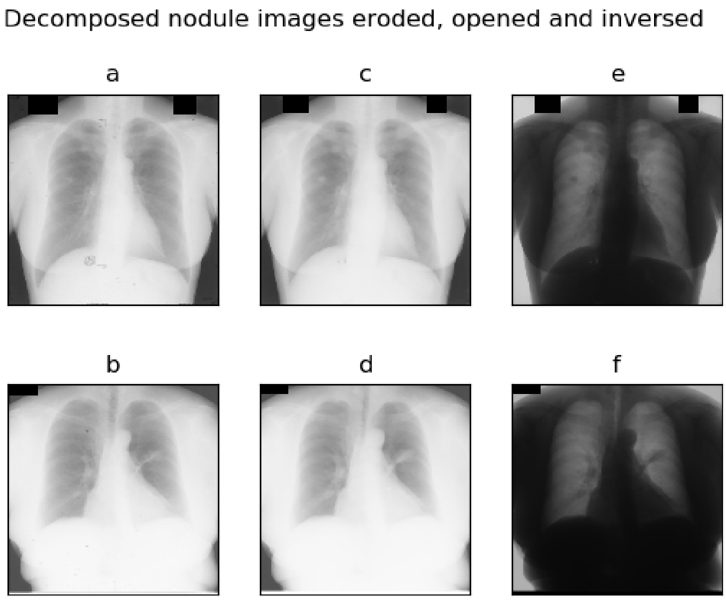

Figure 6. This is part of the sample of images shown in Figure 5. (a-b) are the result of applying morphological erosion to reconstructed chest images with nodules, (c-d) show dilation of the eroded images in (a-b), (e-f) show inverted images of the images in (c-d)

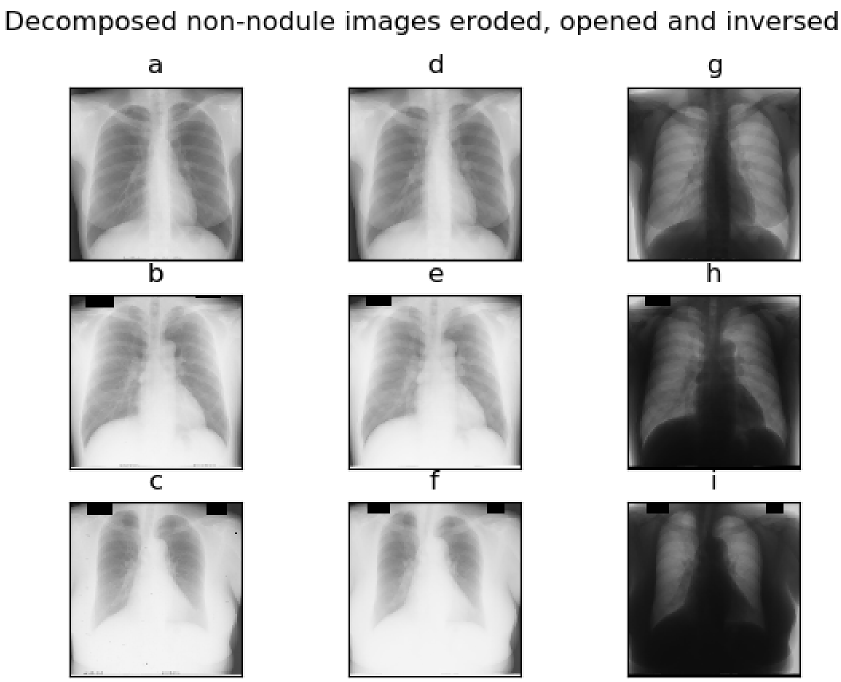

Figure 7. Morphological erosion applied to reconstructed chest images without nodules, (a-c) are the result of applying morphological erosion to reconstructed chest images with nodules, (d-f) show dilation of the eroded images in (a-c), (g-i) show inverted images of the images in (d-f)

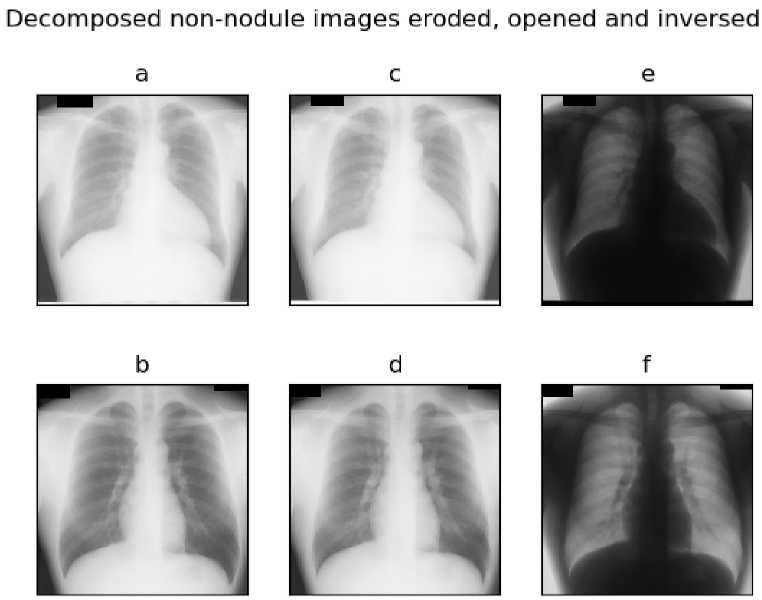

Figure 8. This is part of the sample of images shown in Figure 7. Morphological erosion applied to reconstructed chest images without nodules,(a-b) are the result of applying morphological erosion to reconstructed chest images without nodules, (c-d) show dilation of the eroded images in (a-b), (e-f) show inverted images of the images in (c-d)

4. Discussion and Conclusion

We developed a technique for image denoising and enhancement based on a combination of wavelets and morphological erosion and dilation which is presented and applied to a large sample of chest x-ray images, some of which contained cancer nodules in order to enhance the quality and contrast of the x-ray images. Our approach is tested on a number of publicly available chest radiograph images. The combined wavelet based and mathematical morphology technique retains and elucidate more detail image information of interest on both cancer nodules and anatomical structures captured in chest radiographs. The technique not only suppresses unwanted noise, it also preserves the edges of the nodules to enable accurate detection. From the results obtained, we conclude that our technique is efficient and compares favorably with nonmorphological based techniques for chest radiograph image enhancement.

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