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Chest Radiograph Image Enhancement: A Total Variation Approach

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ABSTRACT

Wavelet denoising of medical images relies on the technique of thresholding. A disadvantage of this method is that even though it adequately removes noise in an image, it introduces unwanted artifacts into the image near discontinuities due to Gibbs phenomenon. A total variation method for enhancing chest radiographs is implemented. The approach focuses on lung nodules detection using chest radiographs (CRs) and the method achieves high image sensitivity and could reduce the average number of false positives radiologists encounter.

General Terms

Image Enhancement, Denoising

Keywords

Total Variation, Chest Radiograph, Algorithm, Convolution, Denoising

1. INTRODUCTION

Lung cancer has been identified as one of the most harmful and common cancers. X-ray images (chest radiographs) play a crucial role in aiding early detection and diagnosis of pulmonary nodules in the lungs, because it is the most commonly used image modality for almost all chest diseases, despite the existence of advanced diagnostic three dimensional imaging systems such as the computed Tomography (CT) and Magnetic Resonance Imaging (MRI). As a result they are used routinely in diagnostic test to reveal unsuspected pathologic alterations such as pulmonary nodules [1, 2]. Unfortunately, X-ray images have a low contrast due to the subtle distinction of attenuation coefficients and scatter effect, which makes it difficult to distinguish signals from background. Moreover, nodules can appear anywhere in the lung field and can also be hidden by ribs, the mediastinum and structures beneath the diaphragm resulting in a huge variation of contrast to the background as shown in Figure 1. CRs serve as an early detection system to reveal signs of lung cancer in any X-Ray film captured [3, 4, 5, 6, 7].
A typical CR will capture anatomical structures together with medical diagnostic points of interest as well as being overlaid with noise. Developing appropriate techniques for noise removal and contrast enhancement in chest radiographs is of utmost importance. The objective of this paper is to develop an enhancement and denoising technique that can be used to reduce anatomical and other noises in CRs for better detection, sensitivity, and specificity of any CADD scheme.
The most popular denoising filter approaches used are Gaussian filter [8], bilateral filter [9], anistropic filter [10], median filter [11, 12], spatial domain filtering, frequency domain filtering, histogram processing, morphological filtering, and wavelet-based filtering. These filtering approaches work in specific noises' type and so are not suitable for medical image quality improvements such as the chest radiograph denoising. The wavelet transform denoising [13] of medical images relies on the technique of wavelet thresholding. A disadvantage of this method is that even though it adequately removes noise in an image, it introduces unwanted artifacts into the image near discontinuities [14].
A combination of the wavelet thresholding technique with other methods based on variational principles yields varying success rates [15], usually with the costly defeciency of removing essential details from the image [16]. In the approach represented here, a noisy mage in a simplified form is represented as a function:

$$z(x) = u(x) + n(x) \tag{1}$$

where $u(x)$ is the noise-free image, and $n(x)$ is the noise. The reconstruction of $u(x)$ reduces to the optimization problem of minimizing the function:

$$E(u) = \frac{\lambda}{2}||u - z||^2_{L^2(\Omega)} + R(u) \tag{2}$$

Here, the parameter $\lambda > 0$ is the Lagrange multiplier and $R(u)$ is the regularization functional. The efficiency of this method is controlled by the choice of the regularization functional. Wang and

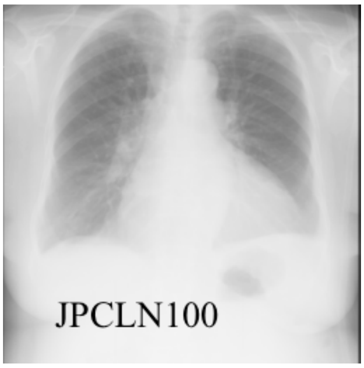

Fig. 1. Chest Radiograph with Certified Nodules

Zhou [14] use the total variation function of the image. That is

$$R(u) = T_z(u) = \int_{\Omega} |\Delta u| dx \tag{3}$$

The regularization term $|\Delta u|$ is designed to remove noise while maintaining salient features and sharp edges [17], and has been shown to lead to sharper reconstruction of the original image [18, 19]. If the Lagrange multiplier λ is small enough, the bounded variation model will efficiently remove the noise [20].
This paper deploys a Total Variation (TV) minimization technique that reduces the oscillations in wavelet thresholding for solving the Gibbs oscillations as well as improve the intensity of the image.

2. TOTAL VARIATION AND IMAGE DENOISING

TV denoising is a method for reducing noise in signals and images and preserving and enhancing edges [21]. The TV methods mentioned above do not consider the effect of noise introduced by the image acquisition system. A denoising algorithm based on the total variation of an image intensity (brightness) function is described. Our method includes a convolution operator which represents the blurring action of the image acquisition system as shown in the figures below. One important advantage of the TV minimization scheme is that it takes the geometric information of the original images into account by preserving and sharpening significant edges [22]. Figure 3 below shows different variational positions during the denoising process in a Matlab based total variational software.

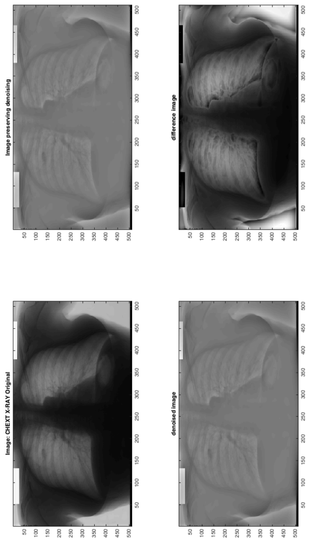

Fig. 2. Convoluted Total Variation

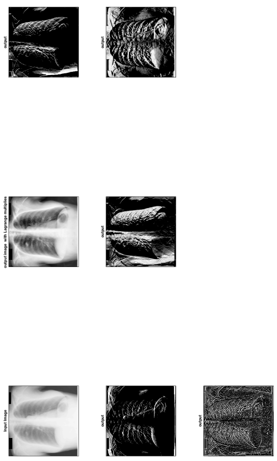

Fig. 3. Total Variation and Noise Blurring Reduced

2.1 Concept of Total Variation

If $f(x)$ be a real valued function. and $P = \{-\infty < x_0 < x_1 < ... < x_n, n \in N\}$ is a partition of the interval $[x_0, x]$, the total variation T_f of f may be defined by:

$$T_f(x) \ = \ sup\{\sum_{i}^{n} |f(x_i) - f(x_{i-1})| : -\infty < x_0 < x_1$$

$$< \ ... < x_n, n \in N\} \tag{4}$$

If $\lim_{x \longrightarrow \infty} T_f(x)$ is finite, then is of bounded variation. The total variation for an L^1 function f of several variables, in an open subset Ω of R^n, is defined as by:

$$\begin{aligned} T_f(x) \ &= \ sup\{\int_\Omega f(x) div\phi(x) dx : \phi(x) \\ &\in \ C_c^1(\Omega, R^n), ||\phi||_{L^\infty(\Omega)} \leq 1\} \end{aligned} \tag{5}$$

The definition becomes simpler if f is a differentiable function defined on a bounded open domain $\Omega \subset R^n$. In this case, the total variation of $f(x)$ is expressed as:

$$T_f(x) = \int_\Omega | \bigtriangledown f(x)| dx \tag{6}$$

The total variation of an image is defined by the duality: for $u \in L^1_{loc}$ the total variation is given by $T_f = sup\{-div\phi dx : \phi \in C_c^\infty(\Omega; R^N), |\phi(x)| \leq 1 \, \forall x \in \Omega\}$.

2.2 The Total Variation Method

This approach represents a noisy image by a function of the form $z(x) = u(x) + n(x)$ where $u(x)$ is the noise-free image, and $n(x)$ is the noise. The reconstruction of $u(x)$ reduces to the optimization problem of minimizing the function.

$$E(u) = \frac{\lambda}{2} ||u - z||^2_{L^2(\Omega)} + R(u) \tag{7}$$

Here, the parameter $\lambda > 0$ and $R(u)$ is the regularization functional and z is defined on the domain Ω. The disadvantage of this methods is that despite removing noise adequately it is removes essential details from the image. This is usually costly in medical imaging since the efficiency of this method is controlled by the choice of the regularization functional. The suggested choice by Zhou et al. is the use of the total variation of the image function. That is

$$R(u) = T_z(u) = \int_\Omega |\nabla u| dx \tag{8}$$

This is the denoising case of the Rudin-Osher-Fatemi problem [23] given by

$$Min_u \lambda T_z(u) + \frac{1}{2} \int_\Omega |u(x) - z(x)|^2 dx \tag{9}$$

It may be shown that the solution of the optimization problem above is equivalent to the solution of the associated Euler-Lagrange partial differential equation of the form [24]:

$$\nabla \cdot \left(\frac{\nabla u}{\nabla} \right) - \lambda(u - z) = 0 \tag{10}$$

Since the optimization problem is strictly convex, it has a unique solution [25, 26].
We extend the Rudin-Osher-Fatemi model to denoising with a blurring convolution operator. This leads to the following optimization problem:

$$Min_u \lambda T_z(u) + \frac{1}{2} \int_\Omega |h * u - z|^2 dx \tag{11}$$

where h is the convolution operator.

3. EXPERIMENTAL RESULTS

An X-ray Images Database of a set of 247 Chest X-ray images obtained from Standard Public Database, the Japanese Society of Radiological Technology (JSRT) is used in this work. This database is selected due to the variety of cases included. The posterior anterior chest films are 34.6 cm by 34.6 cm, (14 by 14 inches) from this database were collected from 14 medical institutions by using screen-film systems over a period of 3 years. All nodules were confirmed by CT, and the locations of the nodules were confirmed by three chest radiologists who were in complete agreement. The images were digitized using an LD-4500 or an LD-5500 laser film digitizer (Konica, Tokyo, Japan), with a resolution 0.175mm pixels in size and a matrix of 2048 x 2048, and 4096 or 12-bit gray scale levels corresponding to a 3.5 optical density range. The database consists of 154 images which are confirmed to contain lung nodules and 93 images without lung nodules. One hundred of the 154 contain nodules which are confirmed as malignant and 54 are benign [27]. The CRs were extracted and classified with the WEKA tool, and the Support Vector Machine (SVM) was used and 80% of all the nodules and normal cases of 247 CRs were used in the training set and 20 % as the testing set which yielded averagely 71.9% in sensitivity.
The CRs which contain the nodules were grouped according to its degree of dificulty for detection. Our experiment is designed through matlab classification algorithm to detect nodules from the CRs. There are five main studies (Wei et al [28], Coppini et al [29], Schilham et al [30], Hardie et al [31], and Chen et al [32] from the literature using the JRST on SVM to compare with our work for performance evaluation.
The accuracy of this method is demonstrated in the form of sensitivity, specificity, and accuracy for the total variation enhanced CRs in computer aided design systems. Sensitivity is a measure which determines the probability of the results that are true positive such that a particular CR has nodules. The sensitivity is deduced as:

$$\begin{aligned} Sensitivity \ &= \ \frac{TRUE\ POSITIVES}{TOTAL\ POSITIVES} \\ &=> \ TP/(TP + FN)) \end{aligned}$$

Specificity is a measure which determines the probability of the results that are true negative such that a person does not have the tumor and system to classify as non nodules with the specificity as.

$$\begin{aligned} Specificity \ &= \ \frac{TRUE\ NEGATIVES}{TOTAL\ NEGATIVES} \\ &=> \ TN/(TN + FP) \end{aligned} \tag{12}$$

Accuracy is a measure which determines the probability of how many results are accurately classified. In the training data, prediction is not very useful since the class labels are known. It also shows the real quality or ability of the performance. The method achieves high accuracy rate in Training as well as Testing datasets:

$$Accuracy ==> (TP + TN)/(TP + FP + FN + TN)$$

Table 1 shows the various sensitivities compared to our work.

4. CONCLUSION

This paper described an algorithm for TV denoising and deblurring of two dimensional images in the form of CRs. The results positively and favorably matched with the most studies from Table 1.The TV denoising algorithm was obtained through the solution of an optimization model which includes the total variation of the

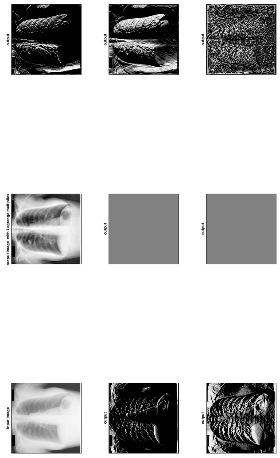

Fig. 4. Convoluted Total Variation

Fig. 5. Total Variation Noise Reduction and Enhancement

image as a penalty function. Here, a noisy image is represented by equation (11). The reconstruction of u from z was posed as a minimization problem in the space of functions of bounded variation $BV(R^2)$ and a convolution operator, which depicts deblurring. Earlier results do not include the deblurring resulting from the image capturing equipment. The algorithm is implemented in MATLAB (TM) with the method implemented here consistently producing quality results. The work focused on on CR image denoising and therefore, did not consider other preprocessing techniques such as image enhancement. In a sequel paper, a combination of

Table 1. Performance comparisons of Sensitivities in Computer Aided detection using JSRT database from the literature

Authors	Sensitivity	Database Usage
Wei et al (2002)	80%	All nodules and normal CRs in JSRT (247)
Coppini et al (2003)	60%	All nodules cases in JRST (154)
Schiham et al (2006)	51% - 67%	All nodules cases in JRST (154)
Hardie et al (2009)	80 % & 63%	Some nodule cases in JRST (140)
Chen et al (2011)	78% , 71.4 %	Some of the nodules and normal CRs case(233
Total Variation Enhanced	79%	All nodules cases of CRs in JSRT(247)

this method and undecimated wavelet algorithm for CR image enhancement will be considered.

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