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A total variation-undecimated wavelet approach to chest radiograph image enhancement

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Abstract

Most often medical images such as X-Rays have a low dynamic range and many of their targeted features are difficult to identify. Intensity transformations that improve image quality usually rely on wavelet denoising and enhancement typically use the technique of thresholding to obtain better quality medical images. A disadvantage of wavelet thresholding is that even though it adequately removes noise in an image, it introduces unwanted artifacts into the image near discontinuities. We utilize a total variation method and an undecimated wavelet image enhancing algorithm for improving the image quality of chest radiographs. Our approach achieves a high level chest radiograph image deniosing in lung nodules detection while preserving the important features. Moreover, our method results in a high image sensitivity that reduces the average number of false positives on a test set of medical data.

Keywords: *chest radiograph, image enhancement, total variation, undecimated wavelet transform*

1. Introduction

Frequency and transform domain techniques [1] such as the discrete wavelet transform (DWT) are able to achieve appreciable results in improving the quality of medical images. How ever, Spatial domain methods used for image denoising and enhancement are not efficient in the extraction and preservation of high frequency components of an image [2]. Even so, the use of the DWT for image enhancement has two main drawbacks. First the DWT is shift variant. Consequently, a small shift in the input signal is magnified in the form of a major variation in energy distribution in the wavelet coefficients at various scales. Another disadvantage is that wavelets lead to directional selectivity of diagonal features of an image since wavelet filters are separable. The objective of this paper is to develop a denoising and enhancement technique that can be used to reduce anatomical and other noises in chest radiographs for better detection sensitivity and specificity of any computer-aided detection and diagnosis (CADD) scheme [3-7]. In our previous work [1], we implemented an algorithm for total variation (TV) denoising and deblurring of two-dimensional chest radiograph (CR) images. The TV denoising filter was effected through the solution of an optimization model which includes the total variation of the image as a penalty function. The observed noisy image was initially assigned the linear representation:

$$z(t) = u(t) + n(t) \quad (1)$$

the reconstruction of u from z was posed as a minimization problem with a convolution operator in the space of functions of bounded variation BV($\mathbb{R}^2$). The convolution operator accounted for the deblurring effect resulting from the image capturing equipment [3], usually ignored in earlier results. We implemented our algorithm in MATLAB (TM) with our method consistently producing quality results. Figure 1 illustrates the difficulty of spotting cancer nodules in chest radiographs with the naked eye.

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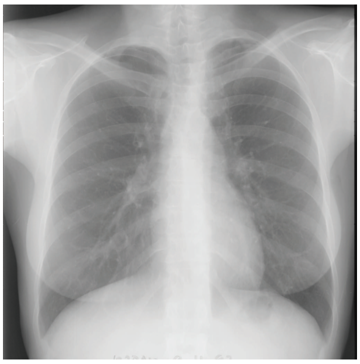

(a) No cancer nodules

(b) With hidden cancer nodules

Figure 1. Typical chest radiographs: (a) without cancer nodules (b) with cancer nodules. Thecancer noudules hidden in (b) are difficult to detect with the naked eye.

Mining to detect nodules in chest radiographs serves as an early detection system to show signs of lung cancer in any X-Ray film captured. Despite these advantages, CR's need enhancement techniques that would reduce the anatomical noise as well as the radiational and quantum noises. The major failure to detect nodules has been attributed to their size and density and mainly to the obscuring anatomical structures which are usually considered as anatomical noise [8]. This paper implements a combined undecimated discrete wavelet transform (UDWT) and total variation (TV) minimization technique. The method achieves a more efficient image denoising and enhancement for CRs than the typical combination of the wavelet thresholding technique with other methods based on variational principles [9, 10]. The TV component achieves the desired image denoising while the wavelet coefficient mapping of the UDWT is used for image enhancement [11]. In addition to improving the visual quality of an image, our hybrid method serves as a preprocessing module for a CAD system. The method is tested on publicly available 247 CR images obtained from JRST.

2. Total Variation Denoising

TV regularization is a deterministic method that minimizes the effect of discontinuities in image processing [12-14]. Standard image processing techniques and algorithmns have the tendency to cause blurring or to lead to contrast loss on the edges of images. Onthe other hand, the TV technique is endowed with the power of preserving and even enhancing the edges [15-18]. The use of TV for image denoising assumes that theobservedimage is madeupof thesum of a piecewise smooth image and guassian noise.

2.1. Total Variation of a Function

Consider a real valued function $f(x)$, representing a signal. Let $P = \{-\infty < x_0 < x_1 < ... < x_n, n \in \mathbb{N}\}$ be a partition of the interval $[x_0, x]$. The total variation T_f of f over the interval is defined by:

$$T_f(x) = sup\{\sum_{i}^{n} |f(x_i) - f(x_{i-1})| : -\infty < x_0 < x_1 < ... < x_n, n \in \mathbb{N}\} \quad (2)$$

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

$$T_f(x) = sup\{\int_{\Omega} f(x) div\phi(x) dx : \phi(x) \in C_c^1(\Omega, \mathbb{R}^n), ||\phi||_{L^\infty(\Omega)} \leq 1\} \quad (3)$$

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

$$T_f(x) = \int_{\Omega} |\bigtriangledown f(x)| dx \tag{4}$$

the space $BV()$ of functions of bounded variation is the set of functions $f \in L^1(\Omega)$ such that $T_f(x) < \infty$. This space can easily be shown to be a Banach space, and is endowed with the norm $||f||_{BV(\Omega)} = ||f||_{L^1(\Omega)} + T_f(x)$

2.2. Total Variation of an Image

The TV method for image denoising has been implemented for several CAD systems [19, 20].

Definition 2.1 *The total variation of an image is defined by the duality: for* $u \in L^1_{loc}$ *the total variation is given by* $T_f = sup\{-div\phi dx : \phi \in C_c^{\infty}(\Omega; \mathbb{R}^N), |\phi(x)| \leq 1 \forall x \in \Omega\}$.

This hybrid approach used here represents a noisy image in a simplified form by (1). The reconstruction of $u(x)$ reduces to the optimization problem of minimizing the function

$$E(u) = \frac{\lambda}{2} ||u - z||^2_{L^2(\Omega)} + R(u) \tag{5}$$

(see for example [17]). Here, the parameter $\lambda > 0$ and $R(u)$ is the regularization functional defined on the domain . The disadvantage of this method is that despite removing noise adequately, it removes essential details from the image [12]. Since the efficiency of the method is controlled by the choice of the regularization functional, this is usually costly in medical imaging. It has been shown that the use of the total variation of the image function below amerolates this problem.

$$R(u) = T_z(u) = \int_{\Omega} |\Delta u| dx \tag{6}$$

This has been shown to lead to sharper reconstruction of the original image by both removing the imbedded noise and better preservation of its edges [21]. An important attribute of the TV minimization scheme is that it takes the geometric information of the original images to account, and this helps to preserve and sharpen the edges significantly [21].

2.3. The Total Variation Technique

Proposition 1 *[16] Let* $K = \{p \in L^2(\Omega) : \int_{\Omega} p(x)u(x)dx \leq T_z(u) \forall u \in L^2()\}$. *If* T is considered *as a functional over the Hilbert space* $L^2(\Omega)$ *we have* $\partial T_z(u) = \{p \in K : \int_{\Omega} p(x)u(x)dx = T_z(u)\}$.

Proof 1 *If* $p \in K and \Omega p(x)u(x)dx = T_z(u)$ *then* $p \in \partial T_z(u)$. *Clearly for any* $v \in L^2(\Omega)$ *we have* $_z(v) = sup_{p \in K} \int_{\Omega} p(x)u(x)dx$. $T_z(v) \geq \int_{\Omega} p(x)v(x)dx = T_z(u) + \int_{\Omega}(v(x) - u(x))p(x)dx$. *Conversely, if* $p \in \partial T_z(u)$, *then for any* $t > 0$ *and* $v \in \mathbb{R}^N$, *with* $T_z(tu) = tT_z(u)$ *since* T_z *is positively one-homogeneous, we have:* $tT_(v) = T_z(v) \geq T_z(u) + \int_{\Omega} p(x)(tv(x) - u(x))dx$. *Dividing by* t *and letting* $t \to \infty \mapsto$ *leads to* $T_z(v) \int_{\Omega} p(x)v(x)dx$. *Hence* $p \in K$. *On the other hand, letting* $t \to 0$ *gives* $T_z(u) \leq \int_{\Omega} p(x)u(x)dx$.

We noted earlier that, the choice of the parameter λ is key to the success of this method. To eliminate the problems presented by trying to figure out the right choice of this parameter, the wavelet total variation scheme is proposed. This method represents the components of the func tion by orthogonal wavelet basis. The wavelet coefficients are then selected to achieve the goals of denoising and enhancement. To achieve our goal, we extend the Rudin-Osher-Fatemi model to denoising with a blurring convolution operator. This leads to the following optimization problem:

$$Min_u \lambda T_z(u) + \frac{1}{2} \int_{\Omega} |h * u - z|^2 dx \tag{7}$$

where h is the convolution operator. In order to detect the edges of nodules from the sorrounding anatomical noise, we apply a Sobel type convolution kernel. This helps to accentuate the edges of the the nodule in the CR image [22].

It can 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 [9]:

$$\nabla \cdot \left(\frac{\nabla u}{|\nabla|} \right) - \lambda(u - z) = 0 \tag{8}$$

since the optimization problem is strictly convex, it has a unique solution. The TV minimization is then combined with the undecimated wavelet image enhancement approach explained in the next section.

3. Undecimated Wavelets Contrast Enhancement and Nodules Detection

Conventional methods of image enhancement such as histogram equalization and gamma adjustment have limited versatility leading to loss of important image features [23]. This is highly fatal in medical imaging applications such as lung cancer detection using chest CRs. Wavelets have become a method of choice for several image processing applications such as denoising and image enhancement since they have the capability of making available spatial frequency information. This property makes it easier to distinguish between noise and real image data.

Wavelet based methods usually outperform traditional methods in improving the edge features in an image [24]. Peng et al. [25] for example, rely on shift invariant WT for contrast enhancement of radiographs. We combine the TV method with UDWT approach of [26] to improve the visual quality of CRs. To eliminate the translation variant drawback of wavelets, the undecimated wavelet transform (UDWT) is applied. Despite the colosal computational storage demands of the UDWT, it gives precise frequency localization information [27]. Even thresholding using only the UDWT improves the results for image denoising by more than 2.5dB [21, 28]. The wavelet model consists of coefficients which are of large magnitudes and are associated with edges and some textures, while the small coefficients are classified as smooth background features. The UDWT is applied with two basic steps: first, the modified UDWT is applied to the medical image, then this is followed by a wavelet coefficient mapping was applied to finally enhance the medical images. The UDWT algorithm is desired to eliminate the translation variant liability of the of the standard DWT. This is achieved by ignoring the downsampling operation of the DWT, leading to the same length for the approximating coefficients and detail coefficients at each level, as the original signal. The resulting gain in image quality far outweighs the storage liabilities for the method on modern computers with vast storage capabilities.

4. Undecimated Wavelet Based Transform Decomposition

We propose a method to automatically extract image texture parameters that can assist in identifying nodule regions for the classification of CRs. Suspected lesion tissues usually hide in low contrast tissue regions and can be localized on local texture features such as texture based undecimated energy. An undecimated wavelet transform decomposition is applied to the CR images and the derived wavelet coefficients are sunsequently used to obtain the local features for the generation of the enhanced energy features. The UDWT produces an exact translational invariance, as well as overcomplete one to one relationship between all colocated coefficients at all scales as against the DWT which is a spatial frequency transform that has been used extensively for texture analysis. A wavelet family such as Bi-orthogonal spline wavelets which provide excellent image scale separation is used. Such wavelets also provide excellent image reconstruction makes it more suitable. Compared with the normal chest X-rays, there are a number of small opacities in the lung anatomical structures, that cause the differences of texture features in CRs with cancer nodules. The nodules are distinguished by using texture features derived from the CRs of lung fields after a series of wavelet transformation.

Using the pyramid decomposition of the two dimensional wavelet decomposition, after decomposition for the first scale, the original image is divided into four subbands, which is expressed by combinations of low and high frequencies. The major texture energy based features are calculated on the 11th scale of four sub bands for each scale. Energy levelcalculation on $l = 1$ to 4 and $k = 1$ to 11 respectively is calculated [15] by:

$$E_k l = 1/M_k * N_k \sum_{i=1}^{M_K} \sum_{j=1}^{N_K} X(i, J)^2$$

where M_k and N_k represent the size of sub-band images of the kth scale. The four sub-band images of the kth scale are of equal size as M_k and N_K and $x(i, j)$ ($i = 1$ to M_K) and $j = 1$ to N_k respectively. is the gray value of pixel (i, j) of the image. The final feature vector contains 44 energy features of wavelet coefficients calculated in sub-bands at successive scales.

The major characteristics to apply is to obtain features which portray scale dependent properties of the CRs. A feature from each subimage is extracted separately, and a non linear function of the coefficients is computed using the fact that the coefficients of the subimage sum to zero. Other studies use alternative measures such as entropy as well as more than one feature. The level 2 wavelet coefficients for a chest radiograph image are calculate in Figure 2.

5. Experimental Results

A database of a set of 247 Chest X-ray images obtained from Standard Public Database, the Japanese Society of Radiological Technology (JSRT) is used to test our algorithm. The set includes posterior and anterior chest films measuring 34.6 cm by 34.6 cm (14 by 14 inches) were collected from 14 medical institutions by using screen-film systems over a period of 3years. 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 0.175 m pixels in size and a matrix of 2048x2048, and 4096 or 12-bit gray scale levels corresponding to a 3.5 optical density range. A total of 154 images are confirmed to contain lung nodules and 93 images without lung nodules. One hundred of the 154 contain nodules which were confirmed as malignant and 54 are benign [29]. 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 an average of 71.9% in sensitivity. The CRs which contain the nodules were grouped according to the degree of dificulty of detection. The results are compared with previous studies [30-34] for performance evaluation. he 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.

$$\begin{aligned} Sensitivity &= \frac{TRUE\ POSITIVES}{TOTAL\ POSITIVES} \\ &= TP/(TP + FN)) \\ Specificity &= \frac{TRUE\ NEGATIVES}{TOTAL\ NEGATIVES} \\ &= TN/(TN + FP) \\ Accuracy &= (TP + TN)/(TP + FP + FN + TN) \end{aligned} \tag{9}$$

The total variation method is applied to denoised and enhanced CR image shown in Figure 3. Table 1 shows the various sensitivity, specificity, and accuracy of the undecimated total variation method compared to a total variation only approach.

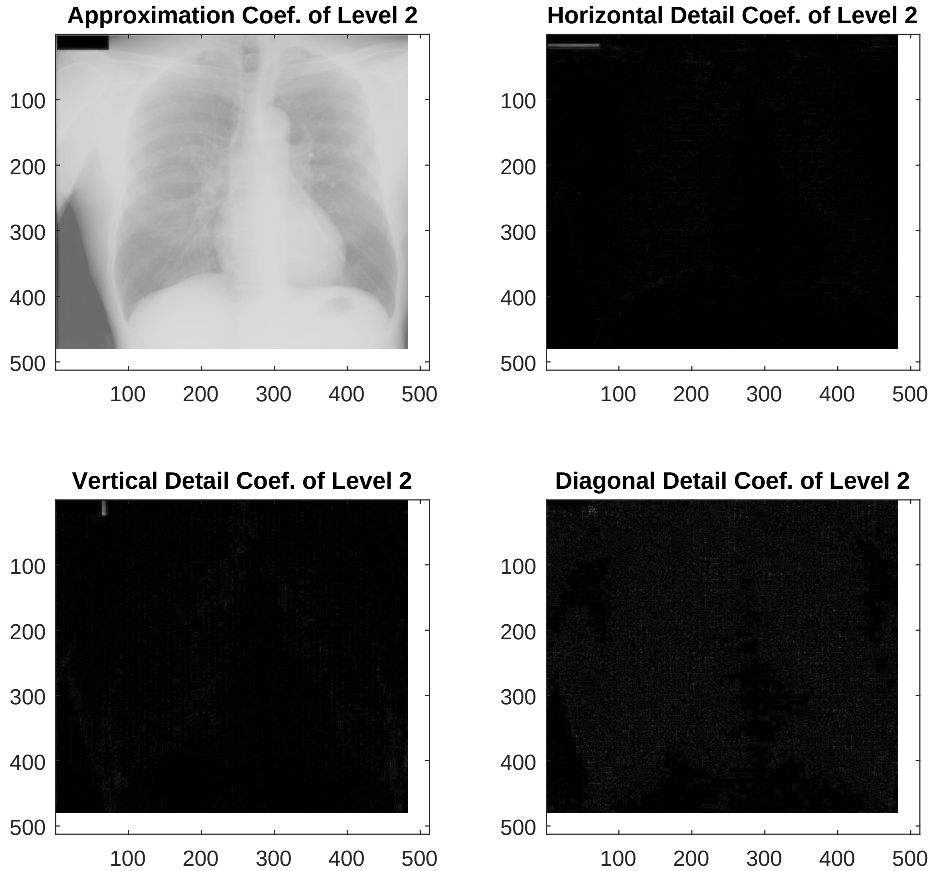

Figure 2. Coefficients of undecimated wavelet transform

Figure 3. A CR image processed with a convoluted total variation method

Table 1. Performance Measures for TV vs TV and UDWT

Method	Sensitivity	Specificity	Accuracy
TV	79.0%	80.0%	91.7%
TV and UDWT	82.5%	93.3%	97.0%

5.1. Image Quality Analysis

We use the peak signal to noise ratio (PSNR) to evaluate the performance of our algorithm, where

$$PSNR = 10log_{10}\left(\frac{I^2_{(m,n)}peak}{MSE}\right) \quad (10)$$

where $I_{(m,n)}peak$ is the peak pixel value in the image $I_{(m,n)}$ and is usually 255 for pixels represented using 8 bits per sample, and MSE is the mean square error. The PSNR we obtained is 42.8dB. This confirms the validity and efficiency of our method.

5.2. Wavelet Based Feature Extraction and Feature Analysis in Digital Chest Radiographs

Feature extraction is carried out after the segmentation algorithm of the lung region. The accuracy in the segmentation algorithm supports the reliability of feature extraction algorithm and the classification algorithm. The features generated convey meaningful information which are subjected to the classification algorithm to determine whether a nodule is detected or not. The characteristics of the detected nodules is used in discriminating malignant from benign nodules. Most nodule infested CRs have a number of small opacities, resulting in the differences of texture features between the normal and the abnormal CRs. The diagnosis of cancer nodules is improved by using texture features derived from CRs of lung fields after a series of wavelet transformations.

Texture features always represent the characteristics of CRs and can be used in classifying CRs into two categories: nodules or non-nodules. There are wellknown methodologies and approaches for texture feature extraction which support identifications below the threshold of human visual perception. Wavelets-based methods possess the superior qualities in discrimination algorithms where preservation is a major concern in the various resolutions [35].

We quantify the characteristics of nodules by mathematical feature descriptors, to give diagnostic indicators and then further classification decides whether nodules detected show signs of malignancy in the CRs image. The feature extraction in our work is based on undecimated wavelet texture analysis (UWTA). The undecimated wavelet transformation involves, filtering with-out subsampling, so unlike the DWT, the UDWT does not incorporate the down sampling opera-tions. Thus, the approximation coefficients (low-frequency coefficients) and detailed coefficients (high-frequency coefficients) at each level are of the same length as the original signal. Based on the UDWT, fourteen texture features of pulmonary nodules on digital CRs were extracted in every sub-image.

We derive the mean and the variance of the energy, distribution of the transform coefficients for each subband at each decomposition level are used to construct the feature set. Normally, pathological changes reflecting in the texture analysis of CRs occur qualitatively and quantitatively. Unfortunately there are no unique ways in accessing texture from medical images since there are different modalities in medical images.

We use the undecimated wavelet based texture analysis with wavelets filters. In wavelet transformation, the energy is distributed in different wavelet coefficients with detail components containing high degree of local relevance. The analysis explores different wavelets families in the over-complete wavelet transform as the UWTA [36, 37]. By removing the downsampling step of the FWT, a translation invariant, overcomplete wavelet decomposition of an CRs image is obtained. Using such a representation when extracting features for texture analysis has the advantages of greater spatial resolution, more robustness against translation, and allowing greater confidence when extracting statistical features of larger number coefficients [38].

Wavelets help solid regions of interest to be extracted with accuracy due to its improved noise level during its pre-processing. It is helpful to improve edge detection since pure pixel based algorithms are prone to noise, using biorthogonal spline based wavelet filters. The wavelet transform perform similar analysis as the human visual system in hierarchical edge detection at multiple levels of resolution [39, 40], and processes an image in a multiscale manner.

6. Discussion and Conclusion

An image denoising method based on the total variation of an image intensity function combined with the UDWT scheme as an image enhancement algorithm is applied to a set of chest X-Ray images, a specified number of which contained cancer nodules. After denoising and enhancement using our technique via a CAD system, a significant reduction in the number of false positives and false negatives were obtained. Our algorithm was able to detect nearly all of the imbedded cancer nodules in the CRs and thus reduce the percentage of false positives assoiciated with the data. From our observations and obtained results, we can conclude that the algorithm is capable of enhancing the local contrast appreciably.

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