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Chapter

Application to Medical Image Processing

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Abstract

Medical images are often corrupted by white noise, blurring and contrast defects. Consequently, important medical information may be degraded or completely masked. Advanced medical diagnostics and pathological analysis utilize information obtained from medical images. Consequently, the best techniques must be applied to capture, compress, store, retrieve and share these images. Recently, the wavelet transform technique has been applied to enhance and compress medical images. This review focuses on the trends of wavelet-based medical image processing techniques. A summary of the application of wavelets to enhance and compress medical images such as magnetic resonance imaging (MRI), computerized tomography (CT), positron emission tomography (PET), single photon emission computed tomography (SPECT), and X-ray is provided. Morphological techniques such as closing, thinning and pruning are combined with wavelets methods to extract the features from the medical images.

Keywords:

1. Introduction

The goal of this chapter is to provide a review of the applications of wavelets to medical imaging. The focus will be on medical image denoising and compression. Advanced medical diagnostics utilize information obtained from technologies such as magnetic resonance imaging (MRI), computerized tomography (CT), positron emission tomography (PET), single photon emission computed tomography (SPECT), and X-ray [1, 2]. However, such images are corrupted by white noise, blurring and contrast defects. Consequently, important medical information may be degraded or completely masked. Recently, wavelet-based techniques have been applied to achieve superior image denoising and economical image compression.

1.1 Wavelet properties in medical imaging: multiresolution analysis

A multiresolution analysis is a decomposition of the Hilbert space $H = L^2(R)$ into a chain of closed subspaces $(V_j), j \in Z$ which form a sequence of successive approximation subspaces of H such that the following hold:

1. $V_j \subset V_{j+1}$ for all $j \in \mathbb{Z}$
2. $\bigcup_{j=-\infty}^{\infty} V_j$ is dense in $L^2(\mathbb{R})$ and $\bigcap_{j=-\infty}^{\infty} V_j = \{0\}$.
3. $f(x) \in V_j \Leftrightarrow f(2x) \in V_{j+1}$ for all $j \in \mathbb{Z}$
4. $f(x) \in V_j \Leftrightarrow f(x - k) \in V_j$ for all $j, k \in \mathbb{Z}$
5. Each subspace V_j is spanned by integer translates of a single function $f(x)$. That is, for any $f \in L^2(\mathbb{R})$ and any $k \in \mathbb{Z}; f(x) \in V_0, f(x - k) \in V_0$. All subspaces are therefore scaled versions of the central space V_0 .
6. (6) There exists a function $\psi(x)$, belonging to V_0 , such that the sequence $(\psi(x - k); k \in \mathbb{Z})$ forms a Riesz basis or unconditional basis for V_0 . Using the result that an orthonormal basis can always be generated out of a given Riesz basis, Riesz basis can be replaced by orthonormal basis.

1.2 Wavelet properties in medical imaging: wavelet bases

One of the special qualities of wavelets which is exploited in medical image analysis is the ability to construct L^2 bases which are simply dilations and translations of a single compactly supported function given by $\{\psi_{j,k} = 2^{-j/2}\psi(x/2^j - k)\}$ where $j, k \in \mathbb{Z}$. This enables any image function f to be represented by:

$$f = \sum_{j \in \mathbb{Z}} \sum_{k \in \mathbb{Z}} c_{j,k} \psi_{j,k} \quad (1)$$

2. Undecimated wavelet transform

Conventional methods for medical image enhancement have very limited versatility in application and their use could lead to the loss of important medical image features of interest. This could be highly fatal in medical imaging applications [3]. The undecimated discrete wavelet transform (UDWT) method is a wavelet transform algorithm without the downsampling operations, resulting in both the original signal and the approximation and detailed coefficients having same length at each level of decomposition. The basic algorithm of the conventional UDWT is that it applies the transform at each point of the image and saves the detailed coefficients and uses the approximation coefficients for the next level. The size of the coefficients array does not diminish from level to level. This decomposition operation is further iterated up to a higher level. Various denoising methods using the DWT provide robust computational methods in denoising digital medical images. The only issue with the DWT is that it is shift variant. This disadvantage can may be ameriorated by using the UDWT to achieve shift invariance.

3. Image enhancement: wavelets and medical image denoising

Medical images are usually corrupted by noise inherrent in the processes of acquisition, trasmission, and retrieval [4, 5]. In particular, medical images such as those

obtained from MRI or X-rays are often complicated by random noise that occurs during the image acquisition stage [6]. Wavelet-based techniques overcome most of these limitations. The objective of enhancement is to remove the effects of signal degradation caused by the signal processing. Noise may be removed by smoothing the signal by subjecting it to a low-pass filter. Sharpening to remove blur is used to identify more detailed features by applying a high-pass filter.

3.1 Wavelets methods

With its inherent properties of multiresolution structure, application of wavelets to medical images converts the noisy image in the time domain into the wavelet transform domain. Subsequently, essential image detail information is compressed into large coefficients that are retained at different resolution scales. The small coefficients represent the noise in the image as well as any redundant information. In medical image analysis, the boundary line between “large” and “small” coefficients is crucial since it determines whether the noise is significantly removed in addition to crucial detail being preserved.

3.2 Hybrid methods for medical image denoising

Spatial filters have the tendency of blurring images since the technique smoothens data in order to remove noise [7]. Tackling this problem by relying on wavelet transform alone sometimes does not satisfactorily address the image enhancement problem since wavelet transform methods are plagued by oscillations, shift variance, aliasing and lack of directionality. Three methods that are combined with wavelets significantly eliminate the problems listed above the medical image enhancement outcomes considered here.

3.2.1 Total variation denoising

Total variation (TV) regularization is a deterministic method that minimizes the effect of discontinuities in image processing [8]. The TV technique is endowed with the power of preserving and even enhancing the edges. The use of TV for image denoising assumes that the observed image is made up of the sum of a piecewise smooth image and gaussian noise.

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

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

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

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

If f is a differentiable function defined on a bounded open domain $\Omega \subset \mathbb{R}^n$ this reduces to:

$$T_f(x) = \int_{\Omega} |\nabla f(x)| dx \quad (4)$$

Definition 3.1 *The total variation of an image is defined by the duality: for $u \in L^1_{loc}$ the total variation is given by $T_f = \sup \{ -\operatorname{div} \phi dx : \phi \in C_c^\infty(\Omega; \mathbb{R}^N), |\phi(x)| \leq 1 \forall x \in \Omega \}$.*

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

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

(see for example [9]). Here, the parameter $\lambda > 0$ and $R(u)$ is the regularization functional defined on the domain Ω . The disadvantage of this method is that despite removing noise adequately, it removes essential details from the image [8]. Since the efficiency of the method is controlled by the choice of the regularization functional, this is usually costly in medical imaging. The use of the TV of the image function below ameliorates this problem.

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

It leads to sharper reconstruction of the original image by both removing the imbedded noise and better preservation of its edges [10, 11]. TV minimization scheme takes the geometric information of the original images into account, and this helps to preserve and sharpen the edges significantly [11].

3.2.2 The wavelet-total variation method

Proposition 1 [12] *Let $K = \{p \in L^2(\Omega) : \int_{\Omega} p(x)u(x)dx \leq T_z(u) \forall u \in L^2(\Omega)\}$. If T_z 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 $\int_{\Omega} p(x)u(x)dx = T_z(u)$ then $p \in \partial T_z(u)$. Clearly for any $v \in L^2(\Omega)$ we have $T_z(v) = \sup_{p \in K} \int_{\Omega} p(x)u(x)dx$. $T_z(v) \geq \int_{\Omega} p(x)v(x)dx = T_z(u) + \int_{\Omega} (v(x) - u(x))p(x)dx$. 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 $t \rightarrow \infty$ leads to $T_z(v) \geq \int_{\Omega} p(x)v(x)dx$. Hence $p \in K$. On the other hand, letting $t \rightarrow 0$ gives $T_z(u) \leq \int_{\Omega} p(x)u(x)dx$.*

Method	Sensitivity	Specificity	Accuracy	PSNR
TV	79.0%	80.0%	91.7%	30.97%
TV and UDWT	82.5%	93.3%	97.0%	42.80%

Table 1.
TV vs TV and UDWT.

Figure 1.
 (Column 1) Original chest images with nodules, (column 2) wavelet decomposition of images in column 1, (column 3) reconstructed images from the decomposed images.

The wavelet TV scheme represents the components of the function by orthogonal wavelet basis. The wavelet coefficients are then selected to achieve the goals of denoising and enhancement (**Table 1**). **Figure 1** shows the results on the chest radiograph images.

The Python 2.7 code is given below.

```

"""A code to implement a wavelet denoising and morphological enhancement
"""

#import math
#import numpy as np

import cv2
import matplotlib as plt import pywt
kernel=cv2.getStructuringElement(cv2.MORPH_ELLIPSE,(11,11))
img1=cv2.imread('JPCLN001.jpg') coeff1=pywt.wavedec2(img1, 'bior1.3')
coeff11=pywt.waverec2(coeff1,'db2')
erosion1=cv2.erode(coeff11,kernel,iterations=2)
opening1=cv2.dilate(erosion1,kernel,iterations=3)
oinv1=1-opening1
fig 1=plt.figure()
fig 1.suptitle('Original, Decomposed and Reconstructed CR Images with Nodules')
    
```



```
plt.subplot(331),plt.imshow(img1),plt.title('a'),plt.xticks([]),plt.yticks([])
plt.subplot(332),plt.imshow(coeff1[0]),plt.title('d'),plt.xticks([]),plt.yticks([])
plt.subplot(333),plt.imshow(coeff11),plt.title('g'),plt.xticks([]),plt.yticks([])
fig 1.savefig('1CR i ages with nodules, decomposed and reconstructed.png')
fig 3=plt.figure()
fig 3.suptitle('Decomposed nodule images eroded, opened and inversed')
plt.subplot(331),plt.imshow(erosion1),plt.title('a'),plt.xticks([]),plt.yticks([])
plt.subplot(332),plt.imshow(opening1),plt.title('d'),plt.xticks([]),plt.yticks([])
plt.subplot(333),plt.imshow(oinv1),plt.title('g'),plt.xticks([]),plt.yticks([])
fig 3.savefig('1Decomposed nodule images eroded, opened and inversed.png')
```

3.2.3 Mathematical morphology

Mathematical morphology (MM) is a technique for extracting image components of interest. Dilation and erosion are the two basic operations in mathematical morphology as well as thinning, opening, closing, and pruning. Wavelets combined with MM has recently been used to improve chest radiographs [13].

Definition 3.2 Erosion and Dilation: Let E be the Euclidean space, let $A : E \subseteq \mathbb{Z}^2 \rightarrow \mathbb{Z}$ be an image and $B : \mathbb{Z}^2 \rightarrow \{0, 1\}$ be a structuring element. The translation of a set C by a point $z = (z_1, z_2)$, denoted by $(C)_z$ is defined as $(C)_z = \{a | a = c + z, c \in A\}$. The erosion of A by B , denoted by $(A \ominus B)$, is expressed as

$$(A \ominus B) = \{z | (B)_z \subseteq A\}, \quad (7)$$

ie. The set of all pixel locations z in the image plane where $(B)_z$ is contained in A .

Definition 3.3 The dilation of A by B is denoted by $(A \oplus B)$ and is expressed as

$$(A \oplus B) = \{z | (\hat{B})_z \cap A \neq \emptyset\}, \quad (8)$$

where $\hat{B} = \{w | w = -b, \text{ for } b \in B\}$ is the reflection of B .

This indicates the set of all pixel locations z in the image plane where the intersection of $\hat{B}$ with A is not empty [14].

Erosion shrinks an image or a region A by a template or a structuring element B . Dilation expands an image or a region A by a template or a structuring element B . The dilation process consists of obtaining the reflection of B about its origin and then shifting this reflection by some displacement x .

Other effects can be obtained by applying erosion and dilation in a loop. Closing and opening are two examples of basic erosion and dilation combinations.

3.3 Opening and closing

Definition 3.4 The opening of A by B , denoted by $A \circ B$, is simply erosion of A by B , followed by dilation of the result by B , that is,

$$(A \circ B) = (A \ominus B) \oplus B. \quad (9)$$

Visually, opening smoothens contours, breaks narrow isthmuses and eliminates small islands.

Definition 3.5 *The closing of A by B, denoted by $A \bullet B$, is a dilation followed by an erosion and is given as*

$$(A \bullet B) = (A \oplus B) \ominus B. \tag{10}$$

Closing smoothens the contours, fills narrow gulfs and eliminates small holes. It is based on these operations that other operations are derived.

3.4 Thinning and pruning

The thinning operation is related to the hit-or-miss transform and it can be expressed in terms of it. The thinning operation is derived by translating the origin of the structuring element to each possible pixel position in the image and comparing it with the underlying image pixels at each such position. Pruning is a post-processing technique that follows thinning. It removes parasitic components known as spurs which are unwanted branches, from the thinned image. There are specific structuring elements used for pruning.

Combined with MM wavelets can be used to decompose a fingerprint image in order to extract the areas with details. The results of this approach is shown in **Figures 2 and 3**.

Algorithm 1
Denoising the fingerprint image
1. Load fingerprint image.
2. Convert the greyscale fingerprint image into a binary image.
3. Decompose image using wavelets into detailed and approximated parts.
4. Reconstruct the fingerprint image using the detailed parts of the decomposed image and set the approximated part to zero.
Algorithm 2
Processing the image for feature extraction
1. Load denoised image.
2. Perform a binary closing on the image to close all insignificant holes in the image.
3. Thin image.
4. Prune the result to remove spurs and spikes.
5. Extract features.

3.4.1 Wavelet K-SVD approach

The wavelet tranform technique (for image denoising) has several advantages such as sparsity, multiresolution structure, and similarity with human vision. Recently, it has been combined with K-Singular Valued Decomposition (K-SVD) algorithm, and an adaptive learning over the wavelet decomposition of a noisy medical image has resulted [15].

Figure 2.
Wavelet analysis and synthesis of image: (a) original image, (b) decomposed image, (c) reconstructed image.

Figure 3.
Morphological operations applied to fingerprint images: (a) original image, (b) binary closing of image, (c) thinned image, (d) pruned image.

4. Wavelet based compression methods for storing medical images

In medical image compression, a mathematical transform is applied to the digital data. This is intended to compress the data for efficient storage, transmission, and

Method	DWT (Haar) [17]	DWT (dB) [17]	DWT and MM
CR	7.40%	21.86%	21.90%

Table 2.
Compression ratios.

retrieval. Compression involves coding and image approximation and helps to reduce the quantity of information, improve the transmission rate and reduce the size of the equipment and storage space required. Data compression requires the choice of a transform such that as many of the transformed data as possible vanish. The ability to localize basis functions in wavelet applications make them suitable for compression. In addition to this property of wavelets, a wavelet decomposition of an image capitalizes on its multiresolution structure, a recursive method to compute the wavelet transform of an image [16]. The three components of the wavelet transform based image are image decomposition, quantization, and decompression.

4.1 Hybrid methods for medical image compression

The DWT combined with vector quantization methods have recently be shown to achieve superior results in medical image compression than wavelet alone technique. For example, Ammah and Owusu [17] proposed an efficient medical hybrid image decompression technique for ultrasound and MRI images. The method consists of first preprocessing the image by noise removal. This is follwed by filtering the image using the DWT with hard thresholding. The image is subsequently vector quantized and then Huffman encoded. The inverse operations are then applied to obtain the decompressed image.

The metrics used to evaluate the efficiency of the compression methods are the compression ratio (CR) and the peak signal to noise ratio (PSNR) given by:

$$CR = \frac{I(x,y)}{I'(x,y)} \tag{11}$$

and

$$PSNR = 20 \log_{10} \left\{ \frac{255}{RMSE} \right\} \tag{12}$$

where the RMSE is the root mean squared error.

Using a new class of spline wavelet filters, more effective data compression techniques have been devised to compress massive quantities of medical image data leading to a more economical storage process and enhanced medical image quality when retrieved. Combined with other methods, the inherrent properties of wavelets such as sparsity and multiresolution structure produce superior medical image data compression results than the competition. CRs for three most used methods are is shown in **Table 2**.

5. Conclusion

Modern radiology techniques are essential in advanced medical diagnostics and pathological analysis [18]. Applications of the wavelet tranform for medical imaging

techniques and current advances in research in this direction has been highlighted in this chapter. This includes the combination of the standard wavelet techniques with TV, MM and other methods.

Acknowledgements

Author Anthony Y. Aidoo acknowledges the support from the CSU-AAUP Faculty Research Fund 2021-22.

Classifications

2020 AMS Subject Classification: 68U10, 94A12, 28A99, 92C55, 65R10, 44A99.

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