Image Noise Removal By Dual Double Density Wavelet Transform Using Matlab

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Abstract: **Advances in computing technology have allowed researchers across many fields of endeavor to collect and maintain vast amounts of observational statistical data such as clinical data, biological patient data, data regarding access of websites, financial data, and the like. This thesis addresses some of the challenging issues on JPEG images caused by the weak correlation between intensity and anatomical meaning. With the objective of utilizing more meaningful information to improve the quality of images an approach which employs bilateral symmetry information as an additional feature for segmentation is proposed. This is motivated by potential performance improvement in the images segmentation systems which are important for many medical and scientific applications we are using double density dual wavelet transform for removal noise by using MATLAB.**

I. INTRODUCTION

Image Resolution enhancement (RE) schemes which are based on wavelets have an advantage over conventional methods which suffer from the losing of high frequency contents which causes blurring. The discrete wavelet transform-based (DWT) RE scheme generates artifacts due to a DWT shift-variant property. A wavelet-domain approach based on double density dual-tree complex wavelet transform (DDDT-CWT) is proposed for RE of the images and compared with dual-tree complex wavelet transform (DT-CWT). An image is decomposed by DDDT-CWT to obtain high frequency sub bands. The high frequency sub bands and the low-resolution (LR) input image are interpolated and the high frequency sub bands are passed through a low pass filter. The filtered high-frequency sub bands and the LR input image are combined using inverse DT-CWT to obtain a resolution-enhanced image. Objective and subjective analyses reveal superiority of the proposed technique over the conventional and state-of-the-art RE techniques

This paper presents an automated method for image denoising which is still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. This paper describes different methodologies for noise reduction (or denoising) giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data given its degraded version. Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise is observed in ultrasound images whereas Rician noise affects MRI images. The scope of the paper is to focus on noise removal techniques for natural images.

Probabilistic models using the statistical properties of the wavelet coefficient seemed to outperform the thresholding techniques and gained ground. Recently, much effort has been devoted to Bayesian denoising in Wavelet domain. Hidden Markov Models and Gaussian Scale Mixtures have also become popular and more research continues to be published. Tree Structures ordering the wavelet coefficients based on their magnitude, scale and spatial location have been researched. Data adaptive transforms such as Independent Component Analysis (ICA) have been explored for sparse shrinkage. The trend continues to focus on using different statistical models to model the statistical properties of the wavelet coefficients and its neighbors. Future trend will be towards finding more accurate probabilistic models for the distribution of non-orthogonal wavelet coefficients.

II.PROBLEM DEFINATION

The key step from the image processing to image analysis is image segmentation; it has an important place in image processing and image analysis. On the other hand, it is possible to make high-level image analysis and understanding as the image segmentation is the target expression based on segmentation, the feature extraction and parameter measurement that converts the original image to more abstract and more compact form.

Image noise is random variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the image sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that obscures the desired information.

The original meaning of "noise" was "unwanted signal"; unwanted electrical fluctuations in signals received by AM radios caused audible acoustic noise ("static"). By analogy, unwanted electrical fluctuations are also called "noise".

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Equations

If the input is an RGB image, it can be of class unit8, unit16, single, or double. The output image I is of the same class as the input image. If the input is a color map, the input and output color maps are both of class double.

Algorithm: The function RGB to Gray converts RGB values to grayscale values by forming a weighted sum of the *R*, *G*, and *B* components:

0.2989 * R + 0.5870 * G + 0.1140 * B

Note that these are the same weights used to compute the *Y* component.
The gradient of a function of two variables, $F(x, y)$, is defined as

$$\nabla F = \frac{\partial F}{\partial x}\hat{i} + \frac{\partial F}{\partial y}\hat{j}$$

and can be thought of as a collection of vectors pointing in the direction of increasing values of F. In MATLAB software, numerical gradients (differences) can be computed for functions with any number of variables. For a function of N variables, $F(x, y, z, \ldots)$,

$$\nabla F = \frac{\partial F}{\partial x}\hat{i} + \frac{\partial F}{\partial y}\hat{j} + \frac{\partial F}{\partial z}\hat{k} + \ldots$$

3.2 Data and Sources of Data

DUAL TREE COMPLEX WAVELET TRANSFORM:

The Dual Tree Complex Wavelet Transform (DTCWT) has been developed to properties of the Fourier transform in the wavelet transform. As the name implies, two wavelet trees are used, one generating the real part of the complex wavelet coefficients real tree and the other generating the imaginary part of the complex wavelet coefficients imaginary tree. The Dual-Tree Complex Wavelet Transform (DTCWT) provides the following properties: -

1. Shift Invariance: - DT-DWT has approximate shift-invariance or in other words, improved time-shift sensitivity in comparison with standard DWT. The reconstructed details at various levels and approximation at the last level have almost uniform shifts for the time-shifted unit step functions. The property of shift invariance makes the DT-DWT well suited for applications such as Motion estimation and Image fusion at various resolution levels.

2. Good Selectivity and Directionality: - DT-DWT gives better directional selectivity in 2-D with Gabour like filters (also true for higher dimensionality m-D). Standard DWT offers the feature selectivity in only 3 directions with poor selectivity for diagonal features, where as DT-DWT has 12 directional wavelets (6 for each of real and imaginary trees) oriented at angles of in 2-D. The improved directionality with more orientations suggests the advantage of DT-DWT in a vide rage of directional image processing applications e.g., texture analysis.

3. Phase Information: - Local phase extraction is possible through analytic interpretation of two parallel trees of DT-DWT. The phase of any given sub-band at a given level can be computed with its corresponding real and imaginary coefficients.

4. Perfect Reconstruction (PR): - The DT-DWT structure follows PR conditions; hence, the original signal can be reconstructed from the transform domain complex wavelet coefficients.

5. Limited Redundancy: - DT-DWT has redundancy of 2:1 (2 m :1) for 1-D (m-D) independent of scales (levels) of iteration. Though DT-DWT structure is expensive than standard DWT, it is significantly less expensive than WP, or nondecimated DWT for the same advantage of reduced shift-sensitivity
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3.3 Data Pre-processing

The JPEG images are subject to various types of noises such as irregularities etc. These noises may degrade the quality of the JPEG image and consequently it cannot provide correct information for subsequent image segmentation and edge detection. In order to improve the quality of the JPEG image, operations need to be performed to remove or decrease degradations suffered in its acquisition. Preprocessing is also needed in order to homogenize and separate the intensity distributions of the malignant and benign tissues. This can be achieved by using several denoising techniques, viz., Gaussian filter, median filter.

- **Image Smoothing**

Image smoothing act as the pre-processing step for image segmentation, as, almost all of the images suffer from the problem of noise effects. So, pre-processing act as an important aid to the every already existing segmentation method, in which specialized filters as described above smooth the image and simplifying it for subsequent segmentation step.

- **Image Contrast Enhancement**

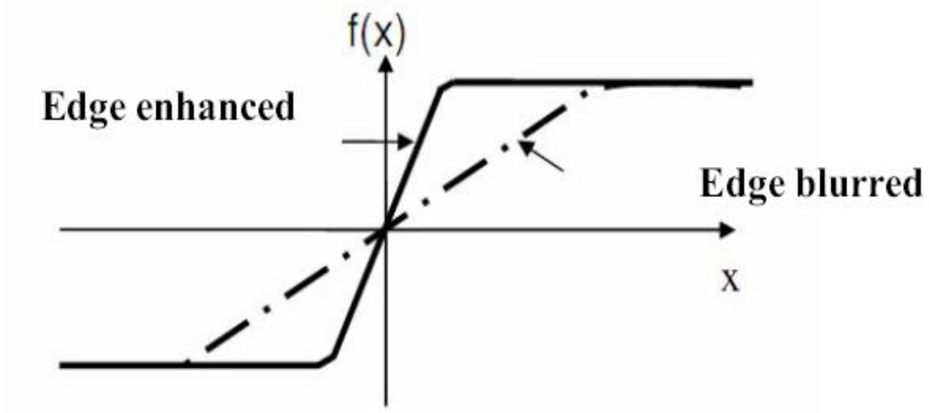
Poor contrast is usually one of the most common defects found in the acquired image. This degradation probably is caused by inadequate aperture size and noise. Sometimes this is caused of nonlinear mapping of the image intensity. The effect of such defects has a great impact on the contrast of the acquired image. In this case, the gray level of each pixel is scaled to improve the contrast of the acquired image. Contrast enhancement step sometimes proves to be one of the important pre-processing steps, especially in case when image has a poor contrast. In the present work, the contrast of the smoothened image is enhanced using the image processing toolbox functions. This improves the visualization of the original image and thus makes the object of interest more clearly visible.

In the first step proper threshold is chosen in order to distinguish the interior area from other organs in the MR image dataset. Then gradient magnitude is computed by using one of Robert, Prewitt or Canny operator and employed as the definition of homogeneity criterion. This implementation allowed stable boundary detection when the gradient suffers from intersection variations and gaps. By analyzing the gradient magnitude, the sufficient contrast present on the boundary region that increases the accuracy of segmentation.

3.4Statistical tools and econometric models

3.4.1 Edge Detection Algorithm

Edge detection techniques transform images to edge images benefiting from the changes of grey tones in the images. Edges are the sign of lack of continuity, and ending. As a result of this transformation, edge image is obtained without encountering any changes in physical qualities of the main image.



3.4.2. System Model

Figure 2.1: Original image

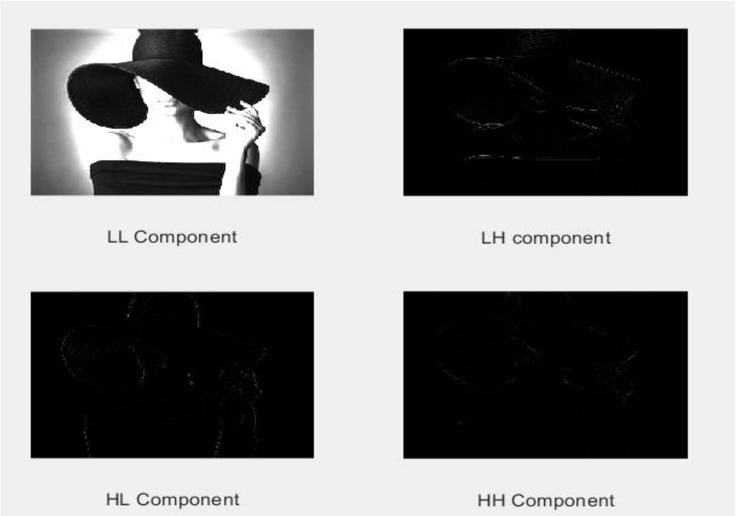


Figure 2.2: Wavelet decomposition

The basic idea of application of wavelet transform is filtering image that is a 2D signal by low pass filter and high pass filter. Low pass filter passes the low frequencies and high pass passes the high frequencies. This is done by the down sampling or up sampling of the image. According to the Nyquist, only half of the frequency samples are enough for faithful reconstruction of the original image. Wavelet reduces the redundancy of the image. Compression of the image totally depends on the image redundancies. Thus, approximated coefficients at first level decomposition carry the most of the information.

3.3 Quality of an Image

The wavelet transform is an invertible transform. After the decryption of an image, an inverse wavelet is applied to get a cover image. The quality of a retrieved audio can find out using quality metrics. The Mean square error (MSE) metric used to compare audio compression quality

Mean Squared Error

MSE: Calculates the mean squared error between processed Image and the original Image. Both Image vectors must be identical.

$$MSE = \frac{\sum [\ I1\ (m, n) - I2\ (m, n)]\ ^\wedge 2}{M * N}$$

Where, M and N are a number of rows and columns.

1 and 2 are the suffixes.

I1(m, n) is the original or reference Image.

I2(m, n) is the processed Image.

Lower the value of MSE, the lower the error.

$PSNR = 10\log10(R^2/MSE)$

IV. RESULTS AND DISCUSSION

At first, the image de-noising naturally corrupted by noise is a classical problem in the field of signal or image processing. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by Gaussian noise using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energies transform values. The wavelet de-noising scheme thresholds the wavelet coefficients arising from the standard discrete wavelet transform. In this paper, it is proposed to investigate the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of PSNR.

Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB, provided the bit depth is 8 bits, where higher is better. The processing quality of 12-bit images is considered high when the PSNR value is 60 dB or higher for 16-bit data typical values for the PSNR are between 60 and 80 dB. Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 dB.

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