Wavelet Based Noise Reduction in Medical Images

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Abstract—Low contrast and poor quality are main problems in the production of medical images. The search for efficient image denoising methods is still a valid challenge at the crossing of various functional analysis. Due to low contrast and high noise in medical images, most algorithms have not yet attained a desirable level of applicability. Wavelet based transformations are used for signal processing such as image compression and denoising. This paper deals with medical image de-noising by using the wavelet analysis focusing on the wavelet thresholding techniques and the threshold estimation. The comparative analysis will then be performed based on the three parameters Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Edge Preserving Index (EPI).

Keywords—Noise; Denoising; Transform; Wavelets; MSE; PSNR; EPI.

I. INTRODUCTION

Enhanced medical images are desired by a surgeon to assist diagnosis and interpretation because medical image qualities are often deteriorated by noise. Medical image enhancement are mainly to solve problems of low contrast and the high level noise of a medical image. Medical image processing mainly based on greyscale transform and frequency domain transform. The wavelet transform is a time-frequency analysis tool developed, which has been successfully applied in the image processing domain after Mallat [1] presented the fast decomposition algorithm. Various enhancement methods based on wavelet transform such as [2][3][4][5] and [6]. This paper presents a comparative study of medical image denoising using wavelet analysis.

A. Noise Model

Imaging sensors can be affected by ambient environments. Interference can be added to an image for the duration of transmission. We can regard as a noisy image to be modelled as bellow:

\[ g(x, y) = f(x, y) + \eta(x, y) \]  \hspace{1cm} (1)

where \( f(x, y) \) is the unusual image pixel, \( \eta(x, y) \) is the noise term and \( g(x, y) \) is the resultant noisy pixel. If we can approximate the model the noise in an image is based on, this will help us to figure out how to re-establish the image. Although these unnecessary fluctuations became known as "noise" by analogy with unnecessary sound they are out of earshot and really beneficial in some applications, such as dithering [7].

B. Image Noise Types

- Gaussian noise- The standard model of amplifier noise is Gaussian, additive, free at each pixel and free of the signal intensity, caused mostly by thermal noise, including that which comes from the rearrange noise of capacitors. In color cameras where additional amplification is used, there can be more noise in the channel. Amplifier noise is a most important component of the "read noise" of an image sensor [8].

- Salt-and-pepper noise - Fat-tail distributed or "impulsive" noise is at times called spike noise or salt-and-pepper noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by ADC errors, bit errors in transmission, etc. Lifeless pixels in an LCD screen produce a like, but non-random, display. This can be eliminated in huge part by using dark/bright pixels.

- Poisson noise- The dominant noise in the lighter parts of an image from an image sensor is characteristically that caused by statistical quantum fluctuations, i.e., variation in the amount of photons sensed at a given disclosure level; this noise is called as photon shot noise. Shot noise have a root-mean-square value relative to the square root of the image intensity, and the noise at dissimilar pixels are independent of one more. Shot noise follows a Poisson distribution, which is usually not very
Unlike from Gaussian. In addition to photon shot noise, there can be current in the image sensor; this noise is sometimes known as "dark-current shot noise" or "dark shot noise".

- **Speckle Noise**: Speckle noise is a multiplicative additional shot noise from the dark leakage noise. This type of noise occurs in almost all coherent imaging systems [9]. The source of this noise is attributed to random interference between the coherent returns. Speckle noise has the characteristic of multiplicative noise and it obey distribution given as

\[
F(g)=\{ g^{a-1}/(\alpha-1)! \, \alpha^a \} \, e^{-\alpha g}
\]

where variance is \(a2\alpha\) and \(g\) is the gray level.

### II. WAVELET TRANSFORM

The wavelet transform WT is the integral transform for time-frequency description of analyzed signal as mentioned in the introduction. It can be used in various signal processing applications, e.g. signal compression, feature extraction, and noise suppression [10]. When considering the analysis of digital images, we may use the two-dimensional dyadic discrete-time wavelet transform 2D-DWT, which uses mother wavelet function \(\varphi\) to decompose a digital image into a multilevel set of approximation and detail (i.e. vertical, horizontal, and diagonal) wavelet coefficient \(c^j_A, c^j_DV, c^j_DH, \) and \(c^j_DD\) where \(j = 1, 2, ..., L\) is the level of decomposition. At each level of decomposition, the approximation wavelet coefficients are decomposed into a new set of approximation and detail coefficients. This can be represented as a frequency sub-band division. The theory of wavelet transform is explained in many publications, a more detailed description of the wavelet transform and its properties can be found, for example, in [11].

#### A. Thresholding Techniques

It comprises the reduction or complete removal of selected wavelet coefficients in order to separate out the noise within the signal. The thresholding method, used in the wavelet based de-noising technique, distinguishes between insignificant coefficients, which are likely due to the noise of magnetic resonance device, and significant coefficients, which consist of important signal components [12]. It is assumed that wavelet coefficients with a value lower than a particular threshold value \(T\) correspond to noisy samples and they can be therefore cancelled, which leads to noise reduction in the image domain. Two basic thresholding techniques are hard and soft thresholding.

When the hard thresholding technique is used, then the wavelet coefficients that are lower than threshold value \(T\) are cancelled and the remaining coefficients are unaffected

\[
\hat{c}(t) = \begin{cases} 
    c(t), & \text{if } |c(t)| \geq T \\
    0, & \text{if } |c(t)| < T 
\end{cases}
\]

The soft thresholding technique cancels the wavelet coefficients that are lower than threshold \(T\), but it also tries to isolate signal from noise in the remaining coefficients by subtracting the threshold value from them

\[
\hat{c}(t) = \begin{cases} 
    \text{sign}(c(t)) \cdot |c(t) - T|, & \text{if } |c(t)| \geq T \\
    0, & \text{if } |c(t)| < T 
\end{cases}
\]

Generally, soft thresholding tends to have a bigger bias due to the threshold of large coefficients, while hard thresholding tends to be of bigger variance and unstable due to discontinuities of the threshold function [13]. But other thresholding methods can be used to obtain a compromise between these two drawbacks.

Semi-soft thresholding is one such method, which solves the problem of discontinuities by introducing two threshold values \(T1\) and \(T2\), where \(T1 < T2\). Wavelet coefficients lower than threshold value \(T1\) are zeroed while coefficients higher than threshold value \(T2\) remain unaffected, and coefficients within the range \((T1, T2)\) are suppressed as shown

\[
\hat{c}(t) = \begin{cases} 
    c(t), & \text{if } |c(t)| \geq T_1 \\
    \text{sign}(c(t)) \cdot |c(t) - T_2|/T_2, & \text{if } T_1 \leq |c(t)| < T_2 \\
    0, & \text{if } |c(t)| < T_1
\end{cases}
\]

#### B. Thresholding Estimation

The most important part of the de-noising algorithm is the estimation of the optimal threshold value. When the threshold value is low, then noise reduction is inefficient. On the other hand, when it is high, then detailed image information can be lost. In our work, we consider one of the most frequently used estimation algorithms, the so-called universal threshold [14].

\[
T = \sigma_{est} \cdot \sqrt{2 \cdot \log(N)}
\]

where \(N\) is the number of input image pixels, \(\sigma_{est}\) represents the standard deviation of noise, which can be estimated by the Donoho and Johnstone theorem [15].

Through the inverse wavelet transform the enhanced image was generated.

### III METHODOLOGY

In medical images many wavelets like db, sym, coif, etc can be used for denoising of a medical image at certain level of soft and hard threshold and then decomposed and reconstructed the denoised image. MSE, PSNR and EPI values are calculated for comparing these wavelets.
IV. RESULTS AND DISCUSSION

This paper also presents a statistical analysis based comparison between Wavelets proposed technique of this paper. The comparative analysis will then be performing based on the three parameters Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and most importantly Edge Preserving Index (EPI). MSE and PSNR are the most important parameters often used for evaluation of image denoising processes and the EPI is very useful to evaluate preservation of edges during image denoising, higher value of EPI indicating higher edge preservation [16].

When comparing compression codes it is used as an approximation to human perception of reform quality, thus in some cases one rebuild may appear to be closer to the original than another, a higher PSNR would normally indicate that the rebuild is of higher quality [17]. One has to be very careful with the range of validity of this metric; it is just conclusively valid when it is used to compare results from the same codec and content. The sparsity analysis is complemented by the quantitative study of partial reconstructions of f, where we have once more used redundancy compensation as explained above. PSNR of best m-term estimate:

$$\text{PSNR} = 20 \log_{10} \left( \frac{\text{max}(f(x)) - \text{min}(f(x))}{||f - f_m||^2} \right) \text{ (dB)}$$   (7)

where fm is the partial rebuild of f using the m biggest coefficients in magnitude, in the wavelet expansion.

$\text{MSE} = \frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{n} |f_{ij} - p_{ij}|^2$    (8)

<table>
<thead>
<tr>
<th>MEDICAL IMAGES</th>
<th>PSNR OF DENOISED IMAGES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar</td>
<td>Daubechies</td>
</tr>
<tr>
<td>X-RAY</td>
<td>43.203</td>
</tr>
<tr>
<td>MRI</td>
<td>44.417</td>
</tr>
<tr>
<td>CT SCAN</td>
<td>60.946</td>
</tr>
<tr>
<td>ULTRASOUND</td>
<td>48.134</td>
</tr>
</tbody>
</table>

TABLE I. COMPARISON OF PSNR VALUES USING THREE DIFFERENT METHODS FOR INPUT IMAGE HAVING GAUSSIAN NOISE
The functions $I_0$ and $I_p$ are original and denoised image, respectively. The no. $m$ and $n$ are the size of an image[16]. Classic values for the PSNR in lossy image and video compression are between 30 and 50 dB, where higher is better. Satisfactory values for wireless transmission quality loss are considered to be as regards 20 dB to 25 dB [17].

**V. CONCLUSION**

Image preprocessing is the most essential and critical part of digital image processing, of many a times even a good algorithm does not provide required result because lack of appropriate preprocessing of the input image. After denoising the images are not able to provide required information needed for the further processing and hence the aim of preprocessing was totally defeated. This problem becomes much crucial in case of medical imaging applications like Ultrasound, Computed Tomography (CT), MRI etc. In such applications all the information are contained in edges, hence after denoising, the output image should contain all the edge information same as input image before denoising. Hence to overcome this problem, in this paper, a highly edge preserving and noise removal image denoising is developed and implemented using newly developed 2Dimensional Discrete wavelet transformation technique in MATLAB for various medical images. For the complete evaluation of developed technique, four different medical images have been used. After implementation of the proposed technique, a statistical analysis based comparison between wavelets filter.

Therefore the developed Wavelet Transformation is not only able to provide much higher noise removal from medical images, as well as it preserves the image quality.

**VI. FUTURE SCOPE**

This research paper mainly emphasizes on the implementation of the denoising techniques to Gray images but in future the same can be applied to color images also. Further the combination of wavelet and curvelet transform can be also used for the aforesaid purpose. New Age Fuzzy Logic can also be incorporated with wavelet technique in this field to take the image processing technology to a whole new level.

**VII. REFERENCES**


