A Detailed Study on Image Denoising Algorithms by Using the Discrete Wavelet Transformation

Asem Khmag, Abd Rahman Ramli, Syed Abdul Rahman Al-Haddad, Shaiful Jahari Hashim

Dept. of Computer and Communication Systems Engineering, Faculty of Engineering, Universiti Putra Malaysia, UPM Serdang, Selangor DarulEhsan, Malaysia
Dept. of Computer Systems Engineering, Faculty of Engineering, Azzawia University, Azzawia, Libya

Abstract
The seeking for an efficient image denoising methods is still a valid challenge at the researches field of image analysis and processing. In spite of the sophistication and extreme researches in the recent years, most algorithms have not yet reach a desirable level of applicability. All the algorithms and methods present a high outstanding performance when the image model corresponds to the algorithm assumptions but it fails in general and create artifacts and blurred texture or change the main structures of the original image. De-noising of natural images corrupted by additive Gaussian noise using wavelet based technique has its effectively performance because of its ability to capture the energy of the signal in few energy transform values or coefficients. This method performs well under a number of applications because wavelet transform has the compaction property of having only a small number of large coefficients where the remaining wavelet coefficients are very small. The aim of this study is to examine a wide range of existing studies in the literature related to applying wavelet transformation for denoising natural images. Furthermore, this study is done to review various denoising algorithms using wavelet transform; those algorithms are discussed with specific details in order to understand the effect of each algorithm on the quality of the image. Algorithms such as SureShrink, Bivariate Shrink, VisuShrink, BayesShrink, Neigh Shrink and Normal shrink are presented in this paper. A different Gaussian white noise levels in PSNR are shown in the experimental results.

Keywords
Discrete Wavelet Transform (DWT), Hard and Soft thresholding, De-noising and Peak Signal to Noise Ratio (PSNR).

I. Introduction
The exigent need for efficient image restoration algorithms has grown with the massive production in fields of video and image processing; in some cases those images are taken in poor conditions such as weather, transmission environmental, impact of the sensors in cameras, resolution and so on. Visual information transmitted in the form of digital images is becoming a major method of communication in the modern technology; unfortunately; the image obtained after transmission is often corrupted with different kinds of noise [1]. The received images need processing before it can be used in different kinds of applications. Image restoration involves the manipulation of the image data to produce a visually high quality image. Over the past decade, wavelet transforms have received a lot of attention from researchers in many several aspects. In the same issue, the discrete wavelet transform also provides multiscale spatial and frequency decomposition. The frequencies can be resolved in space domain and this is very useful in the localization feature of the image that under study. For this reason, it is preferred over other methods such as the Fourier and Cosine transform. This paper present review and details study of image denoising using wavelet based approach, where the additive noise is present in a contaminated image. Gaussian noise is the most commonly known as additive white Gaussian noise which is evenly distributed over the signal. Each pixel in the noisy image is the sum of the true pixel value and random Gaussian distributed noise value [2]. Simple denoising algorithms that use the wavelet transform consist of three main steps. Donoho and his team work present in [3] the following wavelet denoising scheme:
1. Calculate the wavelet transform of the noisy signal.
2. Modify the noisy wavelet coefficients according to threshold \( \lambda \), hard/soft.
3. Compute the inverse transform using the modified coefficients.

Fig. 1 shows block diagram of Donoho algorithm [4].

Bui and Chen [5] proposed a translation invariant multiwavelet denoising scheme that gave better results than [6]. Simoncelli and Adelson [7] propose Bayesian wavelet coring method to reduce the visual artifacts: Gibbs phenomena in the neighborhood of discontinuities. Spurious wavelets can also be seen in the restored image due to the cancelation of small coefficients; this artifact will be called wavelet outliers, as it is introduced in [8]. Mallet and his team members in [9] improved the wavelet thresholding methods by averaging the estimation of all translations of the degraded signal the wavelet coefficients of the original and translated signals can be very different, and they are not related by a simple translation or permutation. Zhuang and Baras [10] studied the problem of choosing an image-based customized wavelet basis with compact support for image data compression and provided a general algorithm for computing the optimal wavelet basis. Second-Generation Wavelets (SGWs) replace dilations and translations with an entirely spatial domain lifting scheme [11] based on the operations of splitting, prediction, and updating. In the SGW setting, only one coefficient per scale is chosen for prediction. [12-13] proposed an adaptive shrinkage denoising scheme by using neighbourhood characteristics. They claimed that their new scheme produced better results than Donoho’s methods.
According to [14], the authors studied and summarized some standard methods that are used adaptive filtering technique to reduce the additive white Gaussian noise impacts. Recent study that have reported in [15] and got promising results in terms of quality and good preserving in the edges of the reconstructed image based on multiple wavelet biases.

The organization of this paper is as follows. Section II reviews different types of wavelet filtering, section III explains several image restoration algorithms using wavelet and threshold method, section IV conducts some experiments to denoise some noisy images and present potential for future research and finally Section V gives the conclusion of this study.

II. Image Filtering Using Wavelet Transformation

In noise-removal area, a well-known signal-processing method is the Fourier transform. It converts a signal into a series of sine curves. Wavelets as well expand a signal but instead of using the smooth cosine and sine waves, apply some basis functions called wavelets. As the wavelet functions are irregular, asymmetric and finite, wavelet analysis can describe the local features, signals with sharp edges, and features better than Fourier analysis [16].

Linear filters such as Wiener filter in the wavelet domain yield optimal results when the signal corruption can be modeled as a Gaussian process and the accuracy criterion is the mean square error (MSE) [14-20]. However, designing a filter based on this assumption frequently results in a filtered image that is more visually displeasing than the original noisy signal, even though the filtering operation successfully reduces the MSE. In [21] a wavelet-domain spatially adaptive FIR Wiener filtering for image denoising is proposed where wiener filtering is performed only within each scale and intrascale filtering is not allowed.

A. Linear Filters

Linear filters such as Wiener filter in the wavelet domain yield optimal results when the signal corruption can be modeled as a Gaussian process and the accuracy criterion is the mean square error (MSE) [14-20]. However, designing a filter based on this assumption frequently results in a filtered image that is more visually displeasing than the original noisy signal, even though the filtering operation successfully reduces the MSE. In [21] a wavelet-domain spatially adaptive FIR Wiener filtering for image denoising is proposed where wiener filtering is performed only within each scale and intrascale filtering is not allowed.

B. Non-Linear Threshold Filtering

The most investigated domain in denoising using Wavelet Transform is the non-linear coefficient thresholding based methods. The procedure exploits sparsity property of the wavelet transform and the fact that the Wavelet Transform maps white noise in the signal domain to white noise in the transform domain. Thus, while signal energy becomes more concentrated into fewer coefficients in the transform domain, noise energy does not. It is this important principle that enables the separation of signal from noise [22]. The procedure in which small coefficients are removed while others are left untouched is called Hard Thresholding [23]. But the method generates spurious blips, better known as artifacts, in the images as a result of unsuccessful attempts of removing moderately large noise coefficients. In order to overcome the demerits of hard thresholding, wavelet transform using soft thresholding was also introduced in. In this scheme, coefficients above the threshold are shrunk by the absolute value of the threshold itself. Similar to soft thresholding, other techniques of applying thresholds are semi-soft thresholding and Garrote thresholding. Most of the wavelet shrinkage literature is based on methods for choosing the optimal threshold which can be adaptive or non-adaptive to the image.

1. Non-adaptive Thresholds

One of the most known algorithms in non–adaptive threshold is VisuShrink [23] which depends only on number of data points. It has asymptotic equivalence suggesting best performance in terms of MSE when the number of pixels reaches infinity. VISUShrink is known to yield overly smoothed images because its threshold choice can be unwarrantedly large due to its dependence on the number of pixels in the image. In the third section of this paper detailed explanations will be presented about VisuShrink.

2. Adaptive Thresholds

SUREShrink uses a hybrid of the universal threshold and the SURE (Stein’s Unbiased Risk Estimator) threshold and performs better than VISUShrink. BayesShrink [24] minimizes the Bayes’ Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptive threshold. BayesShrink outperforms SUREShrink most of the times. Cross Validation [25-26] replaces wavelet coefficient with the weighted average of neighborhood coefficients to minimize Generalized Cross Validation (GCV) function providing optimum threshold for every coefficient. There are two primary thresholding methods: hard thresholding and soft thresholding [20]. Hard thresholding operator is defined as:

\[ f(x) = \begin{cases} 
  x & \text{if } x \geq \lambda \\
  0 & \text{otherwise}
\end{cases} \]

Soft thresholding operator is defined as:

\[ f(x) = x - \lambda & \text{if } x \geq \lambda \\
  0 & \text{if } x < \lambda \\
  x + \lambda & \text{if } x \leq -\lambda
\]

C. Noise Removal Procedure

The pioneering work of Donoho and Johnstone [21] can be summarized as follows. Let g(t) be the noise-free signal and f(t) the signal corrupted with white noise z(t), i.e., f(t) = g(t) + \sigma z(t), where z(t) has a normal distribution N(0; 1). Donoho and his coworkers proposed the following algorithm.

1. Discretize the continuous signal f(t) into fi, i = 1; . . . ; n (e.g., via uniform sampling).
2. Transform the signal fi into an orthogonal domain by discrete single wavelet transform.
3. Apply soft or hard thresholding to the resulting wavelet coefficients by using the threshold $\delta = \sqrt{2\sigma^2 \log n}$.
4. Perform inverse discrete single wavelet transform to obtain the denoised signal.

The denoising is done only on the detail coefficients of the wavelet transform. It has been shown that this algorithm offers the advantages of smoothness and adaptation. However, as Coifman and Donoho pointed out, this algorithm exhibits visual artifacts: Gibbs phenomena in the neighborhood of discontinuities. Therefore, they propose in [6] a Translation-Invariant (TI) denoising scheme to suppress such artifacts by averaging over the denoised signals.

TI denoising suppresses noise by averaging over thresholded signals of all circular shifts. The TI table is a fast way of implementation, rather than having to do a transform on the original signal n times. We can realize the TI multiwavelet denoising algorithm in the following steps:

1. Apply Prefilter on the original noisy signal by a specific prefilter.
2. Decompose the multiple streams into a TI table that is similar to the TI table in [6].
3. Apply the univariate or bivariate thresholding (soft/hard) on the TI table.
4. Calculate the denoised multiple streams from the TI table by reversing the processes in Step 2.
5. Postfilter the denoised multiple streams to get the denoised signal.

According to the preceding discussion, there are four criteria that will be taken into account in the comparison of denoising methods:

- A display of typical artifacts in the reconstructed images.
- A formal computation of the method noise on smooth images, evaluating how small it is in accordance with image local smoothness.
- A comparative display of the method noise of each method on real images with certain value of the standard deviation $\sigma$.
- A classical comparison receipt based on noise simulation: it consists of taking a good quality image, adding Gaussian white noise with known $\sigma$, and then best image recovered can be computed from the noisy one by each method.

On top of this, in some cases, a proof of asymptotic recovery of the image can be obtained by statistical arguments.

D. Soft and hard thresholding

The threshold plays an important role in the denoising process. Figure 2 demonstrates the hard and soft thresholding functions. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value loses the coefficients that carry image signal details. Normally, hard thresholding and soft thresholding techniques are used for such de-noising process. Hard thresholding is a keep or kill rule whereas soft thresholding shrinks the coefficients above the threshold in absolute value. It is a shrink or kill rule. Famous algorithms will be presented and explained in details in the next section [27].

![Fig. 2: (a) Hard Threshold, (b) Soft Thresholding Functions](image)

This kind of shrink uses soft thresholding and its subband-dependent, which means that thresholding, is done at each band of resolution in the wavelet decomposition. It is smoothness adaptive like the SureShrink procedure. The Bayes threshold, $t_B$, is defined as:

$$t_B = \frac{\sigma^2 \log n}{\sigma_s^2}$$ (4)

where $\sigma^2$ is the noise variance and $\sigma_s^2$ is the signal variance without noise. The noise variance $\sigma^2$ is estimated from the subband HH1 by the median estimator shown in Equation (5). From the definition of additive noise [28]

$$\sigma_n^2 = \frac{\text{median}([HH1])^2}{0.6745}$$ (5)

From the definition of additive noise we have

$$w(x,y) = s(x,y) + n(x,y)$$ (6)

Since the noise and the signal are independent of each other, it can be stated that

$$\sigma_w^2 = \sigma_s^2 + \sigma_n^2$$ (7)

Its computed as shown below:

$$\sigma_w^2 = \frac{1}{n^2} \sum_{x,y=1}^n w^2(x,y)$$ (8)

III. Wavelet Denoising Algorithms

A. Bayes Shrink

BayesShrink was proposed by Chang, Yu and Vetterli [30]. The goal of this method is to minimize the Bayesian risk, and hence its name, the variance of the signal, $\sigma_s^2$ is computed as

$$\sigma_s = \sqrt{\max(\sigma_w^2 - \sigma_s^2, 0)}$$ (9)

With $\sigma^2$ and $\sigma_s^2$, the Bayes threshold is computed from Equation 4.10

B. Normal Shrink

The optimum threshold value for the Normal Shrink (TN) is given by [29]:

$$t_n = \frac{\sigma_s^2}{\sigma^2}$$ (10)
Let $g = \{g_k\}$ be defined as:

$$ \text{TN} = \frac{\lambda \sigma^2}{\sigma_y}, $$

(10)

Where, the parameter $\lambda$ is given by the following equation:

$$ \lambda = \sqrt{\frac{\log(\frac{1}{2})}{J}}, $$

(11)

$L_\text{s}$ is the length of the sub-band at $k^{\text{th}}$ scale. And, $J$ is the total number of decomposition. $\sigma_y$ is the estimated noise variance, calculated by (5) and $\sigma$ is the standard deviation of the sub-band of noisy image, calculated by using (8). Normal Shrink also performs soft thresholding with the data driven sub-band dependent threshold $\text{TN}$, which is calculated by the equation (10).

### C. Neigh Shrink

Let $g = \{g_k\}$ will denote the matrix representation of the noisy signal $[31-32]$. Then, $w (Wg)$ denotes the matrix of wavelet coefficients of the signal under consideration. For every value of $w_{ij}$, let $B_{ij}$ is a neighboring window around $w_{ij}$ and $w_{ij}$ denotes the wavelet coefficient to be shrinked. The neighboring window size can be represented as $L \times L$, where $L$ is a positive odd number. A $3 \times 3$ neighboring window centered at the wavelet coefficient to be shrinked is shown in fig. 3.

![3x3 window B_{ij}](image)

**Fig. 3:** An Illustration of the Neighbouring Window of Size $3 \times 3$ Centered at the Wavelet Coefficient to be Shrunk

Let:

$$ s_i = \sum_{(k,l) \in B_{ij}} W_{kl} $$

(12)

The corresponding terms will be omitted in the summation when the above summation has pixel indexes out of the wavelet sub-band range. The shrinked wavelet coefficient according to the Neigh shrink is given by this formula [33].

$$ W'_{ij} = \frac{1}{\beta_{ij}} W_{ij} $$

(13)

The shrinkage factor $\beta_{ij}$ can be defined as:

$$ \beta_{ij} = \left(1 - \frac{T_{UNI}^2}{S_{ij}^2}\right)^{+} $$

(14)

Here, the $+$ sign at the end of the formula means to keep the positive value while set it to zero when it is negative and $T_{UNI}$ is the universal threshold, which is defined as [4]:

$$ T_{UNI} = \sqrt{2 \sigma^2 \ln(n)} $$

(15)

Where $n$ is the length of the signal. Different wavelet coefficient sub-bands are shrinked independently, but the universal threshold $T_{UNI}$ and neighboring window size $L$ kept unchanged in all sub-bands. The estimated denoised signal $f' = f_{ij}'$ is calculated by taking the inverse wavelet transform of the shrinked wavelet coefficients $W_{ij}'$ i.e. $f' = W^{-1} W'_{ij}$.

### D. VisuShrink

The VisuShrink technique consists of applying the soft thresholding operator using the universal Threshold (15): As originally proposed by Donoho and Johnstone [34].

Note that VisuShrink is found to yield an overly smoothed estimate, especially in the case of the soft thresholding operator. This is because the universal threshold, $T_{UNI}$, tends to be too high for large values of $n$ in equation (15), setting to zero many signal coefficients along with the noise. This illustrates a common limitation of VisuShrink which has been widely reported in the literature [3-21]. The main feature of VisuShrink is that it guarantees a highly smoothed reconstruction of the noisy image but in doing so it often compromises many of the important features of the image (i.e. edges) by setting the threshold conservatively high. These limitations of VisuShrink are also due to the fact that it fails to adapt to the various types of statistical and structural properties of the wavelet tree. The universal threshold is applied uniformly throughout the wavelet tree. However, the use of different thresholds for different decomposition levels and sub-bands seems more reasonable.

### E. SURE Shrink

A threshold chooser based on Stein’s Unbiased Risk Estimator (SURE) was proposed by Donoho and Johnstone [21] and is called as SureShrink. It is a combination of the universal threshold and the SURE threshold. This method specifies a threshold value $t_j$ for each resolution level $j$ in the wavelet transform which is referred to as level dependent thresholding [29]. The goal of SureShrink is to minimize the mean squared error, defined as [30].

$$ \text{MSE} = \frac{1}{n^2} \sum_{x,y=1}^{n} (s(x,y) - z(x,y))^2 $$

(16)

Where $s(x,y)$ is the estimate of the signal while $z(x,y)$ is the original signal without noise and $n$ is the size of the signal. SureShrink suppresses noise by thresholding the empirical wavelet coefficients. The SureShrink threshold $t^*$ is defined as:

$$ t^* = \min(t, \sigma \sqrt{2 \log n}) $$

(17)

Where $t$ denotes the value that minimizes Stein’s Unbiased Risk Estimator, $\sigma$ is the noise variance computed from (7), and $n$ is the size of the image. SureShrink follows the soft thresholding rule. The thresholding employed here is adaptive, i.e., a threshold level is assigned to each dyadic resolution level by the principle of minimizing the Stein’s Unbiased Risk Estimator for threshold estimates. It is smoothness adaptive which means that if the unknown function contains abrupt changes or boundaries in the image, the reconstructed image also does.

### F. Bivariate Shrink

New shrinkage function which depends on both coefficient and its parent yield improved results for wavelet based image denoising [27]. Here, then modify the Bayesian estimation problem as to take into account the statistical dependency between a coefficient and its parent. Let $w_{ij}$ represent the parent of $w_{ij}$ ($w_{ij}$ is the wavelet...
coefficient at the same position as \( w_1 \), but at the next coarser scale.) Then
\[
y_1 = w_1 + n_1 \tag{18}
\]
\[
y_2 = w_2 + n_2 \tag{19}
\]
Where \( y_1 \) and \( y_2 \) are noisy observations of \( w_1 \) and \( w_2 \) and \( n_1 \) and \( n_2 \) are noise samples, it can be written as:
\[
y = w + n \tag{20}
\]
\[
y = (y_1, y_2) \tag{21}
\]
\[
w = (w_1, w_2) \tag{22}
\]
\[
n = (n_1, n_2) \tag{23}
\]
According to Bayes rule allows estimation of coefficient can be found by probability densities of noise and prior density of wavelet coefficient. Assume that noise is Gaussian then it can be written as:
\[
p_h(n) = \frac{1}{\pi} \pi(\sigma^2_n) e^{-n_1^2/n^2_1 + n_2^2/n^2_2} \tag{24}
\]
This equation is equivalent to solving following equations
\[
y_1 - \frac{w_1}{\sigma_1} + f_1(w) = 0 \tag{25}
\]
\[
y_2 - \frac{w_2}{\sigma_2} + f_2(w) = 0 \tag{26}
\]
Here \( f_1 \) and \( f_2 \) represent the derivative of \( f(w) \) with respect to \( w_1 \) and \( w_2 \) respectively. It is clear to know \( f(w) = \log(pw(w)) \)
\[
f(w) = \log(pw(w)) \tag{27}
\]
\[
w = \left( \frac{\sqrt{y_1^2 + y_2^2} - \sqrt{3} \sigma_2}{\sigma_1} + y_3 \right) \tag{28}
\]

### IV. Experimental Results

Experiments have been conducted using Matlab prompt. The testing images are Lena and Barbara with size 256 × 256 at different noise levels \( \sigma = 10, 20, 30 \) and 35. Figs. 4, 5 show the noise-free images, the same image with noise added, the denoised image with VisuShrink, the denoised image with NeighShrink, the denoised image with Bivariate, and the denoised image with Bayes filter for images Barbara and Lena, respectively. It is not difficult to see that Night and Bivariate shrinks produce smoother and clearer denoised images than other denoising methods tested in this paper. For some case, choosing the VisuShrink filter and NeighShrink threshold gives us differences range (2.2 to 1.20 dB) improvement over the other methods as its clear visually from the figures and computationally from tables 1, 2. The wavelet mother function that is used in this experiment is Symlets wavelet where it is also known as (Daubechies least-asymmetric wavelets) with 8 vanishing moments and the universal threshold as it in (15). This indicates that the Bivariate shrink threshold makes significant improvement. The improvement of NeighShrink over VisuShrink is even bigger because we combine the advantages wavelet coefficient dependency and Sparsity the customization of the wavelet filter and threshold. We correlate the types of images and noise levels with our proposed method here. The improvement of NeighShrink over VisuShrink is nearly the same for both tested images whether the noise level is low or high. However, the results that achieved whatever the image texture is simple or complicated are in high quality whether the noise level in the contaminated image is high or low. The next equation (29) used to calculate the Peak Signal To Noise Ratio (PSNR) that is used to measure the quality of the reconstructed image.

\[
PSNR = -10 \log_{10} \frac{\sum_{i,j} (B(i,j) - A(i,j))^2}{n^2 \cdot 256^2} \tag{29}
\]
Where \( A(i,j) \) is the noise-free image, \( B(i,j) \) represent the image corrupted with additive white Gaussian noise and \( 256 \) is the image size.

**Table 1: PSNR (dB) of the Noisy Images of Lena and the Denoised Images with Different Denoising Methods**

<table>
<thead>
<tr>
<th>Noisy Image</th>
<th>VisuShrink</th>
<th>NeighShrink</th>
<th>Bayes Shrink</th>
<th>NormalShrink</th>
<th>SureShrink</th>
<th>Bivariate Shrink</th>
</tr>
</thead>
<tbody>
<tr>
<td>28.14</td>
<td>26.35</td>
<td>33.80</td>
<td>32.34</td>
<td>33.53</td>
<td>33.47</td>
<td>33.61</td>
</tr>
<tr>
<td>22.12</td>
<td>23.88</td>
<td>30.38</td>
<td>28.26</td>
<td>30.35</td>
<td>30.07</td>
<td>30.18</td>
</tr>
<tr>
<td>16.10</td>
<td>22.31</td>
<td>25.08</td>
<td>24.64</td>
<td>27.89</td>
<td>27.63</td>
<td>27.94</td>
</tr>
<tr>
<td>12.58</td>
<td>21.53</td>
<td>23.30</td>
<td>22.94</td>
<td>25.32</td>
<td>25.09</td>
<td>25.40</td>
</tr>
<tr>
<td>11.24</td>
<td>21.23</td>
<td>22.74</td>
<td>22.36</td>
<td>23.22</td>
<td>24.42</td>
<td>24.22</td>
</tr>
</tbody>
</table>

**Table 2: PSNR (dB) of the Noisy Images of Barbara and the Denoised Images with Different Denoising Methods**

<table>
<thead>
<tr>
<th>Noisy Image</th>
<th>VisuShrink</th>
<th>NeighShrink</th>
<th>Bayes Shrink</th>
<th>NormalShrink</th>
<th>SureShrink</th>
<th>Bivariate Shrink</th>
</tr>
</thead>
<tbody>
<tr>
<td>28.14</td>
<td>27.85</td>
<td>31.01</td>
<td>33.05</td>
<td>30.74</td>
<td>32.46</td>
<td>33.51</td>
</tr>
<tr>
<td>22.12</td>
<td>25.81</td>
<td>30.87</td>
<td>28.97</td>
<td>25.05</td>
<td>28.14</td>
<td>31.38</td>
</tr>
<tr>
<td>18.60</td>
<td>23.78</td>
<td>29.41</td>
<td>26.77</td>
<td>21.60</td>
<td>26.20</td>
<td>28.60</td>
</tr>
<tr>
<td>16.10</td>
<td>22.98</td>
<td>28.55</td>
<td>25.33</td>
<td>19.11</td>
<td>24.82</td>
<td>27.94</td>
</tr>
<tr>
<td>14.14</td>
<td>22.34</td>
<td>27.22</td>
<td>24.26</td>
<td>17.17</td>
<td>24.79</td>
<td>26.51</td>
</tr>
<tr>
<td>12.58</td>
<td>21.50</td>
<td>22.01</td>
<td>23.40</td>
<td>15.58</td>
<td>22.18</td>
<td>25.09</td>
</tr>
<tr>
<td>11.24</td>
<td>20.70</td>
<td>22.12</td>
<td>22.68</td>
<td>14.23</td>
<td>21.97</td>
<td>23.89</td>
</tr>
</tbody>
</table>
A. Possibility for Future Research
After the discussion and explanation that is mentioned earlier, we can notice a certain points about types of wavelet thresholding (hard, soft). Hard wavelet threshold method noise is concentrated on the edges and high frequency features where the wavelet coefficient processed by the threshold value have discontinuous point on the threshold \( \lambda \) and \(-\lambda\), which may cause Gibbs shock to the useful reconstructed signal. These structures lead to coefficients of large enough value but lower than the threshold, they are removed by the algorithm. On the other hand, the soft wavelet threshold method noise presents much more structure than the hard thresholding, but when the wavelet coefficients are greater than the threshold value, there will be a constant bias between the wavelet coefficients that have been processed and the original wavelet coefficients, making it impossible to maintain the original features of the images effectively.

The literature search revealed that a lot of research has gone into using deferent imaging techniques based on wavelet approaches via hard and soft thresholding. There is a lack of integration of the hard and soft techniques as mentioned above, however, it is evident from the fact that we can not completely eliminate the noise from the contaminated image, but on the other side of this fact we can reduce it as much as we can. The promising results of the new proposed method that we are working on is mainly depends on the semi-soft thresholding technique, where it can reduce the noise efficiently and improve the quality as well as the quantity of the contents of the image, furthermore, in this algorithm a compromise has to be found between noise reduction and preserving significant signal details such as the high frequency details and flat regions in the image. In order to achieve a good performance in this respect, a denoising algorithm has to adapt to use the cycle spinning and signal discontinuities especially in non-repeated, contours, texture and flat object structures.

V. Conclusion
In this study, we have summarized and implemented various effective denoising algorithms based on wavelet schemes for the purpose of image denoising and restoration and assessed their performances. Soft thresholding has been used in the experiments in order to provide smoothness and better edge preservation at same time as it is clear from figs. 4 & 5. Moreover, the experimental results showed that in most cases Bivariate Shrink method gives better results than VisuShrink, NormalShrink. It should be mentioned that in some cases NeighShrink method presented outperformance among the other methods especially when the PSNR of the noisy image lies in the range between 13-18 dB.

References


Asem Khmag was born in Tripoli, Libya. He received B.Sc. degree from University of Tripoli and M.Sc. degree from Universiti Putra Malaysia both in computer and communication systems, in 2003 and 2006, respectively. From 2009 to 2012, he was a lecturer at Azzawia University and researcher in the center of applied science research in Azzawia city. Currently, he is working towards PhD degree at Embedded Systems Engineering Laboratory, department of computer and communication systems, Universiti Putra Malaysia. Kuala Lumpur, Malaysia. His research interests include image processing, pattern recognition, computer vision, and application of computer graphics, cryptography and security systems.

Syed Abdul Rahman Al-Haddad, he received B.Sc. degree in computer Science (Major: Software Engineering), University Technology Malaysia, MSc. in Multimedia Engineering, University Putra Malaysia, Malaysia. And PhD in Electrical, Electronic and System Engineering, Universiti Kebangsaan Malaysia, Malaysia. He has a membership in World Academy of Science, Engineering and Technology (WASET), International Association of Engineers (IAENG), Malaysia Science Engineering Technology (MSET), Malaysia Information Technology Society (MiTS). He is interested in Speech Processing, Office Automation, Computer Telephony and Integration Image Processing.

Shaiful Jahari Hashim, he received B.Eng. with Honor in Electronics and Communication Engineering, University of Birmingham, UK., M.Sc. in Electrical and University of Birmingham, U.K., MSc in Electrical and Electronics Engineering, National University of Malaysia, Malaysia, and Ph.D. in RF Measurement System, Cardiff University, UK.. He is interested in Network Security (Intrusion Detection), Non-linear RF, Microwave and Wireless Measurement System (Load-Pull), Fourth Generation Wireless Network (Wimax), Embedded System.