

Robust Natural Image Denoising in Wavelet Domain using Hidden Markov Models

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Abstract

Background/Objectives: Noise reduction is an essential step in visual improvement task and it plays a major role in subsequent processing tasks such as image analysis. Thus, the main purpose of image denoising especially in natural image is to suppress the artifacts which destroy an image and suppress the additive Gaussian noise without losing the delicate texture of the latent image. **Methods/Statistical Analysis:** Basically, the major the noise which attained in the processes of acquisition and diffusion of several digital images is presumed to be AWGN. Accordingly, a novel framework is proposed based on lifting scheme approach in wavelet domain by utilizing hidden Markov model. In this context, statistical model which is represents by HMM plays a prominent role. It is due to the ability to capture the dependencies and the correlations between the coefficients in different decomposition levels. **Findings:** The extensive experiments prove the efficiency of SGWs-HMM in several standard images when compared with best state-of-the-art noise removal methods. SGWs-HMM shows high competitive performance in terms of visual quality and subjective assessments with the widely used denoising techniques. **Application/Improvements:** This approach shows comparable improvement in subjective and objective assessments. Regarding to the computation complexity, the proposed algorithm is more expensive than rest of algorithms under investigation due to the statistical structure of the proposed method.

Keywords: Hidden Markov Models, Gaussian Noise, Noise Removal, Probability Density Function, Wavelet Transforms

1. Introduction

The image denoising arena has shown an enormous amount of studies during the past decennium, and as a result, a lot of directions were visited effectively. Theoretically, image restoration techniques often consider the contaminated image as stationary format type. It means that the image statistics, such as the mean, the power and the power spectrum are time invariant. On the other hand, great number of natural images are non-stationary with some smooth regions and singularities^{1,2}. This study is essentially focused on improving the quality of the contaminated image in transform domain and with

utilizing of statistical models for the task of image noise removal.

The main aim of image noise removal techniques is to recover images with pleasant visual appearance from the one that has contaminated features via restoration approaches. In this regard, realm of image restoration shows a huge number of implementations: removal of different noise models, image de-blurring, up-scaling, and image super-resolution, in-painting to name a few³.

Different transform domain techniques were used to perform a denoising procedures, discrete wavelet transforms^{4,5} is the core of the denoising and image restoration processes in most of the recent works due to

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the powerful tools that the wavelet provide. The signal that analyzed with wavelet transforms will still keep its features and properties after the decomposition process. Wavelet transforms analyze an image signal into two main parts, namely Details and approximation based on sub-bands. Additionally, a specific wavelet mother function and number of decomposition levels and the type of thresholding function must be clarified when the image restoration takes place. From practical side of view, the wavelet analysis is known as double digital filter channels which have two filter models, lowpass and highpass models. Firstly, the lowpass filter models reflect the approximation of the image at a specific decomposition level, the other model is the highpass filter where it achieves the image details which mostly a result of the difference of the following approximations^{6,7}. Furthermore, the compact property of wavelet shows its efficiency in image restoration and compressions where wavelet coefficients with large amount show large wavelet coefficients in the same sub-band and vice versa⁸. The justification behind this fact can be stated as follows: most coefficients in the sub-band have the significant higher order correlations under the same sub-band under investigation even though when the coefficients reflect uncorrelated manner. In addition, a robust covariance can be found in the amplitude among inter/ intra scale coefficients in the several sub-band levels. In the same issue, huge number of studies has paid attention to inter/ intra scale coefficients in image restoration problem.

Another method called Singular Value Decomposition with k-clustering (K-SVD)^{9,10} shows a good performance using dictionary learning scheme by adopting the noisy image with the use of Discrete Cosine Transform (DCT) as preliminary dictionaries. In this method, every group of pixels may be characterized by a series of groups that belongs to the dictionary or it can be addressed as similar patches in locally learned dictionaries¹¹. Furthermore, Nonlinear Methods (NLM) are used commonly in signal restoration due to the non-stationary property¹². According to the abrupt change in the signal, the principle issue is to substitute the pixels with a weighted average of its counterpart that belong to the same neighborhoods. The core difference between NLM and the mentioned earlier techniques is that NLM exploits merits of the signal correlation in a non-local style. Namely, to scan the full image or patches of the images instead of scan only small areas as local filters do.

Fortunately, statistical techniques show a high performance in order to deal with the burden of taking

the dependencies among several wavelet coefficients by utilizing common statistical approaches. Accordingly, a Hidden Markov Model (HMM), is considered as state of the art model to capture the dependencies among hidden states and parameters is used in this paper. HMM in wavelet transform domain are multi-dimensional in Gaussian mixture techniques, and as a result, the hidden states have a configuration associated with Markovian manner. Thus, the core point is to achieve full dependency of discrete wavelet coefficients that belong to its hidden structure¹³. Generally, the HMM uses the pixels dependency in the image in order to evaluate the quickly reduction when the distance of two adjacent pixel these two pixels increases. The usage of HMM can be seen as a method to find the correlation dependencies between a pixel and its neighbors in the same zone. In this study, SGWs-HMM is used due to the strong correlation between the statistical and wavelet model to solve the issue of natural image restoration. The main aim of this paper is to build a model for natural image noise removal that exploits the spatial properties of HMM. In this regard, the main contributions of this paper are essentially to come up with a compromise base between high visual appearances resulted image and high speed processes according to time consuming matter.

The remainder of this paper is designed as follows. Section 2 reviews and investigate SGWs transforms and its applications. Section 3 presents in details HMM and its impact on the estimation and evaluation of discrete wavelet components. To clarify the main outcome and the details of the suggested technique, Section 4 shows the main parts of the proposed thresholding and evaluation assessments. The main quantitative and qualitative results are shown in section 5. Finally, Section 6 draws the pivotal conclusion and the main suggestions that may improve this study.

2. Second-generation based Wavelet Domain

From a transformation standpoint, the wavelet functions are mainly non-smooth and non-periodic signals. Moreover, they are scaled and translated forms of a single basic wavelet, namely, a mother wavelet. In the 2D wavelet transform framework that is shown in Figure 1, every square represents a sub-band of wavelet coefficients in different levels (every separate group in Figure 1 is known also as a sub-image).

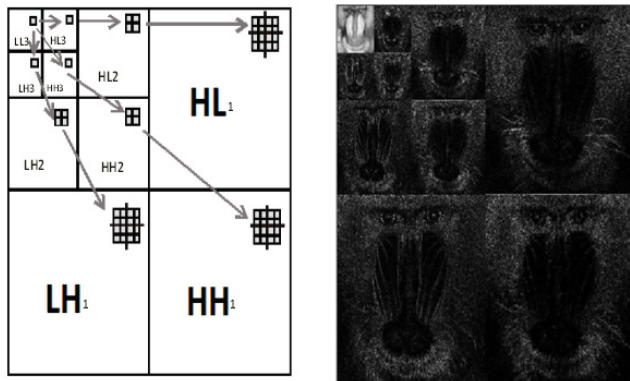


Figure 1. Three levels parent child relationship of the three levels 2-D orthogonal wavelet transformation for Baboon benchmark image.

Classical wavelets that are dyadic dilations and translate of a single function are known as first generation wavelets. A study presented by¹⁴ proposed a new technique, named lifting method, which became the main tool of second-generation wavelets (SGWs). SGWs are not necessarily translates and dilates of one fixed function. In contrast, first generation wavelets that utilize Fourier transforms which is mainly built in a frequency domain, a lifting construction is totally spatial. Consequently, it is practical choice for building SWGs when Fourier transforms cannot be applied.

The aim of this study is to use SGWs based denoising technique to retrieve a high quality natural image from the noisy one. In addition, by utilizing the features of SGWs high speed denoising algorithm will be achieved.

In this technique the signal spectrum splits in two equal parts by passing through two filters called low-pass and high-pass filters. This procedure is represented another perspective to the procedure that mentioned in Figure 2, the main difference is the use of Z-transform in the mathematical calculation. The decomposition filters are noted h_a and g_a and the two synthesis filters are noted h_s and g_s . The main property necessary for a filter bank is the property of perfect reconstruction. After a decomposition followed by a reconstruction without any intermediate operation the output will be equal (possibly up to a translation d) to the value of input^{15,16}. A necessary and sufficient condition links the four filters h_a, g_a, h_s and g_s to obtain a perfect reconstruction with a translation of d in order of time units.

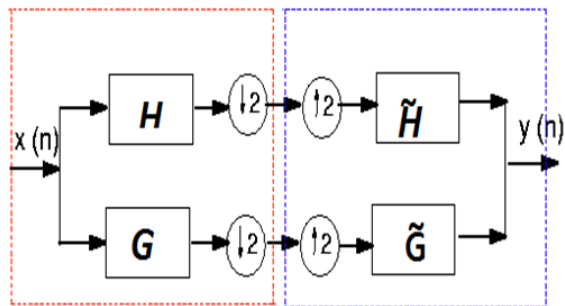


Figure 2. Decomposition and synthesis filters of second-generation wavelet.

3. Denoising-based Hidden Markov Model

The idea behind image restoration with HMM models are to apply the SGWs to the noisy coefficients the main parts of this algorithm is as follows: the contaminated image is transformed to be in SGWs format in order to separate the high and low frequency components. Secondly, the separated coefficients of the contaminated image classified as random parameters and variables to the Gaussian mixture model distribution¹⁸. In the same issue, the hidden structures that are presented from the observed signal are considered to be in mass function likelihood and it represents the weights of each component in the mixture model. Finally, HMM is exploited to adapt the hidden states to be connected to very state in order to catch the correlation among inter/intra scale levels of the wavelet coefficients^{18,19}. The pseudo-code of our optimal SGWs-HMM is presented in Figure 3. In order to investigate the AWGN effects on noisy natural image, let the noise-free image be $\{x_{i,j}, i, j = 1, \dots, N\}$ where, (i, j) represents the pixel location of the noise-free image, it is formulated in mathematical equation such as:

$$y_{i,j} = x_{i,j} + n_{i,j} \tag{1}$$

where, $y_{i,j}$, $x_{i,j}$ and $n_{i,j}$ represent the noisy image wavelet coefficients, the original image and the AWGN respectively. $n_{i,j}$ is considered as independent, Identically Distributed (iid), The term “independent” shows that the joint Probability Density Function (pdf) of the combination of the noise values may be written as the

product of the probability density functions of the individual noise components at the different pixels. The term “identically distributed” means that the noise components at all pixel positions come from identical probability density functions. Thus, $n_{i,j}$ is standard $N(0, \sigma_n^2)$ and not associated of $x_{i,j}$. The pivotal objective is to eliminate the unwanted parts from $y_{i,j}$, or “denoise” $y_{i,j}$ and achieve an evaluation form of $\hat{x}_{i,j}$ of $x_{i,j}$ which reduces MSE as shown in Equation (2).

$$\xi = \text{Min}(x - \hat{x})^2 \tag{2}$$

On the other hand, the MSE(ξ) estimation that reflects minimum value of MSE stated as conditional evaluation to the well-known statistical model of Gaussian noise distribution as follows:

$$E[X_i | Y_i, S_i = j] = \frac{\sigma^2_{x_{i,j}}}{\sigma^2_{x_{i,j}} + \sigma^2_n} * y_i \tag{3}$$

where, $x_{i,j}$ and $y_{i,j}$ represents the random variables of $x_{i,j}$ and $y_{i,j}$ correspondingly $y_{i,j}$, S_i represents the hidden structure of the output y_i . Thus, the noisy image in this part will be demonstrated according to the statistical estimation of HMM. As a result, the signal variance of $x_{i,j}$ will be achieved indirect way. According to the statistical theory, the variance of the contaminated image can be achieved using the analysis tools of the contaminated image where the added variance that is associated to the white noise can be directly eliminated.

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Procedure of Hidden Markov model in SGWs
Input: A is an array of n wavelet coefficients a1, a2, ..., an where an is a parent coefficients.
       B is an array of m wavelet coefficients b1, b2, ..., bm where am is a child coefficients.
Output: Return Ex as the estimated coefficients from HMM estimated factors.
Step 1.
// since the wavelet coefficients A, B in each sub-band is correlated, the coefficients
that have higher value in a parent sub-band A for 0 ≤ i ≤ a_np - 1 //
(1) For i=0 To a_np - 1 Do in Parallel
(2) For j=1 To b_mc - 1 Do
(3) If a_p(i) > b_c(j)
(4) a_p(i) = a_p(i) // ("indication to edge, ridge or other high frequency component") //
(5) else if
(6) a_p(i)=0 or a_p(i) < 0 // assign 0 or lower than 0 //
(7) b_c(j) = b_c(j) // "indication that the child coefficients is low or zero value too" //
(8) j++
(9) end for
(10) end for // end parallel for
Step 2.
// calculate the Expectation-Maximization (EM), that can be used to modify the wavelet
coefficients in the semi-soft criterion according to the threshold function //
(1) For i=0 To a_np - 1 Do in Parallel
(2) For j=1 To b_mc - 1 Do
(3) EM(i, j) = (sigma^2_{x_{i,j}} / (sigma^2_{x_{i,j}} + sigma^2_n)) * y_i // x is the original image, y is represented the
observed image, sigma is the standard deviation //
(4) Est_C = EM(i, j) * B_ij // B_ij is the new coefficients after applying semi-soft
thresholding
(5) end for
(6) end for // end parallel for
Step 3.
(1) For i=0 To Est_C - 1 Do in Parallel
(2) W^1(Est_C) // apply the inverse wavelet on the estimated coefficients.
(3) end for
(4) end
    
```

Figure 3. Pseudo-code of Hidden Markov model in SGWs.

Consequently, the natural digital image X in the statistical models can be studied as a realization of a random field where the PDF function $f(X)$ represent the natural of the input continues signal(image). The probability density function of the signal X for couple of values in range of n and m where $n < m$, can be expressed as:

$$p(n < x < m) = \int_n^m f(x) dx \tag{4}$$

The function of likelihood of the input signal X which is lasts on range of $[n, m]$ can be represented by the area that its position above this interval period and at the same time it lies under the density function graph. Figure 4 shows the density graph of the probability function, in this figure the minimum MSE is seen as a single points which represented by pixels in the contaminated image. In contrary, the main issue of image restoration is based on the density function $f(X)$. The essential objective of statistical image restoration is to find a realistic model which give an approximation to the $f(X)$ and allows effective processing to the denoising technique. Therefore, many techniques are addressed the models of joint statistics of the image patches in local and spatial domain as well, using Markov random field¹⁸ that is the most predominant. The framework of this study is shown in Figure 5.

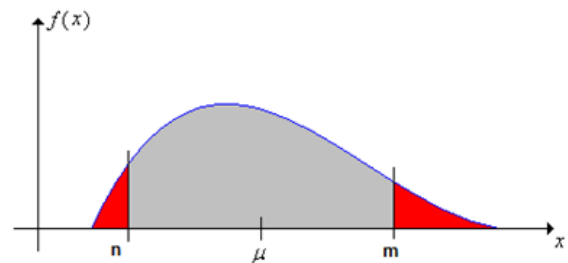


Figure 4. Probability density function of a Gaussian random variable.

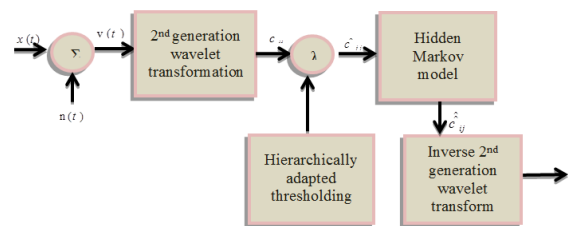


Figure 5. Block diagram for the proposed denoising technique.

4. Methodology

This section will describe and discuss the main steps of the denoising algorithm and state the proposed method performance analysis with more elaboration.

4.1 Framework of SGWs-HMM

The main steps in the SGWs-HMM are stated below:

- The SGWs is applied to the contaminated image $y(t)$.
- Apply kind of multiresolution coarser to finer levels adapted thresholding on the wavelet coefficients $c_{i,j}$.
- The evaluated wavelet coefficients $c_{i,j}$ is achieved via block HMM and its mold on sub-bands. It can be achieved by applying Eq(3).
- The invers SGWs transform is applied to the estimated coefficients $\hat{c}_{i,j}$. This step allow the resulted image to be in the final format and can be studied as denoised image $\hat{x}(t)$, the main parts of the proposed noise removal paradigm is depicted in Figure 3.

From a mathematical side of view, wavelet coefficients are mainly associated in very small neighbourhood. Therefore, the large value coefficients will probably have large coefficients in its small area. Accordingly, the proposed thresholding technique can be found from the neighborhood coefficients of the noisy. We assume that $R_{i,j}$ is the SGWs coefficients of the sub-band under test. Then we consider:

$$U^2_{i,j} = R^2_{i,j-1} + R^2_{i,j} + R^2_{i,j+1} \quad (5)$$

where, $U^2_{i,j}$ is resulted from mathematical summation the coefficients after taking its square, the position of the coefficients is in located in the same position of the coefficient to be shrunk and (i,j) is representing the coefficients position in the degraded image. Based on the conditional inequality that showed in Equation (6):

$$\text{If } U^2_{i,j} < \lambda^2 \quad (6)$$

The target coefficient $R_{i,j}$ then will set to be zero. Otherwise, it will shrink based on:

$$R_{i,j(New)} = \frac{R^2_{i,j} - R^2_{i,j} * \lambda^2}{U^2_{i,j}} \quad (7)$$

where, $\lambda = \sqrt{2 \ln M_j} \sigma_w$, and σ_w represents variance of the noise and M_j is represented the coefficients size of the sub-band under investigation. The modified coefficients

will be found in order to the HMM estimation of the modified coefficients. In order to return to the original domain, the inverse SGWs will be applied to the updated coefficients in order to achieve target (denoised) image.

4.2 Subjective Quality Assessment of SGWs-HMM

The assessments of the denoising algorithm which presented in this paper will be in two main parts. Subjective assessments that is done by the visual appearance of the resulted image and the objective assessments by mathematical models and statistical approaches such as Mean Squared Error (MSE), Structure Similarity Index (SSIM) and Peak Signal to Noise Ratio (PSNR)²⁰.

One of the most common image quality measures is the MSE. In spite it does not always correlate with human perception, the MSE is often considered as an “acceptable” measure of the fidelity of an image estimate. Furthermore, MSE carries the most significance as far as noise suppression is concerned. Let I be the original image, K - denoised image, i, j - pixel row and column index respectively. Its expression is defined by:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \quad (8)$$

Peak signal to noise ratio is measured in decibels. In addition, it is scaled in the criteria of bits per trial or sample, or it can be considered as bits per pixel scale. For instance, if the tested image has 8 bits per pixel, it can be represented with pixel scale from 0 to 255. Greater PSNR value reflects better image quality and noise suppression.

PSNR is derived as:

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX^2}{MSE} \right) \quad (9)$$

The measurement using SSIM scale in the regard of fidelity was taken researchers concern where the images mainly tend to be highly structured²⁰. Namely, the highly correlated pixels tend to be in the small regions of the image.

$$SSIM(X,Y) = [l(X,Y)]^\alpha [c(X,Y)]^\beta [s(x,y)]^\gamma \quad (10)$$

It is important to notice that $\alpha > 0$, $\beta > 0$, and $\gamma > 0$, those factors are used to prioritize the components.

$$SSIM(X,Y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_x\sigma_y + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (11)$$

represents the cross standard deviation amongst the noise free image and the noisy one, w : represents the circular symmetric Gaussian weighting function, and c_1 , c_2 and c_3 are the three constant to prevent instability. Practically, the denoised image scoring the highest SSIM value is the one having the lowest MSE.

5. Results and Discussion

This section will show the main results and state the discussion about the image denoising using HMM in wavelet domain. The vital point in this study is to attain high visual image quality from the contaminated counterpart. Additionally, reducing the execution time is one of the main objectives of this paper as well where the proposed algorithm sows high speed processes to accomplish the denoising steps. In the experiments, SGWs-HMM is applied on three different standard images (Boat, Baboon and Lena) with image size 512x512 as shown in Figure 6, under ($\sigma= 10$ to 30). The database which the benchmark images were image taken from is Berkeley segmentation dataset. (Due to the space limit, the full results cannot be shown here).

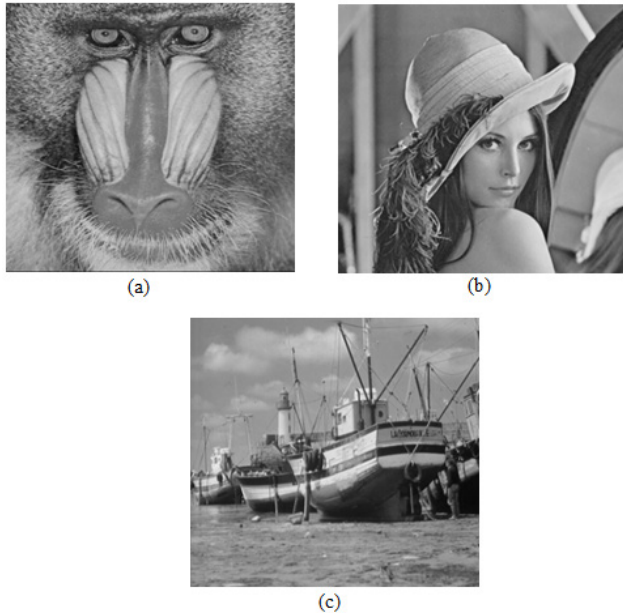


Figure 6. Standard testing images that used in the experiment, images (a) Baboon, (b) Lena and (c) Boat.

In addition, wavelet families of Symmlet, Coiflet and Daubechies are used in this study to represent the

wavelet mother function. From our experiments we have found that Symmelet wavelet (Sym8) shows better results than the other two families due to its perfect regularity, compactly and full symmetry features. In the same regard, four wavelet levels is applied in the wavelet thresholding and the HMM analysis. The geometric features of the tested images such as circles squares and lines are well taken into account in our experiments as well. According to the output analysis of the experimental results, the results are compared in terms of qualitative assessments PSNR and SSIM and by qualitative assessment using the optical view of the resulted images.

However, the denoising algorithms which applied in this paper are: Wiener2 (5 x 5), it is chosen due to the ability to deal with the coefficients that associated with different scales. Another filter model is SureShrink, it is one of the filters that uses the minimizing Stein's Unbiased Risk Estimate (SURE) individually to each synthesis scale in wavelet domain²¹, the NeighLevel²², it exploits the variance of both levels the dependencies in the interscale and its neighbour. BayesShrink²³ one of the simple algorithms it is effective in natural and medical images. Finally, Gaussian Mixture model, it is a statistical model related to the Gaussian scale distribution, the use of this filter is to confirm the relation between the statistical and mathematical models this filter is provided by Portilla in²⁴.

The SSIM is listed in Table 1. From this table it is clear to find that the proposed algorithm showed high performance compared to the several techniques in different range of noise scales. SSIM showed very close results for different algorithms in several images. In Lena benchmark image, the SSIM lasts in the range between (0.8214 to 0.9517). On other hand, SSIM in Baboon was 0.6802 to 0.9303 where the image was full of fine details and may it considered as noise in other filters. Figures 7, 8 and 9 depicted the PSNR of different noisy images. Surprisingly, from Figure 7 we can notice that the proposed technique carries about 0.5 to 1.3 dB enhancements in comparison with state-of-the-art image restoration methods. As a result, the proposed method shows high quality images with preserving the high frequency components and edges in different nose levels and types. On the other hand, filters like BayeShrink, SureShrink and Wiener2 have the PSNR which reflects the same values as the Figure 7 depicted especially in the noise levels of 20-25.

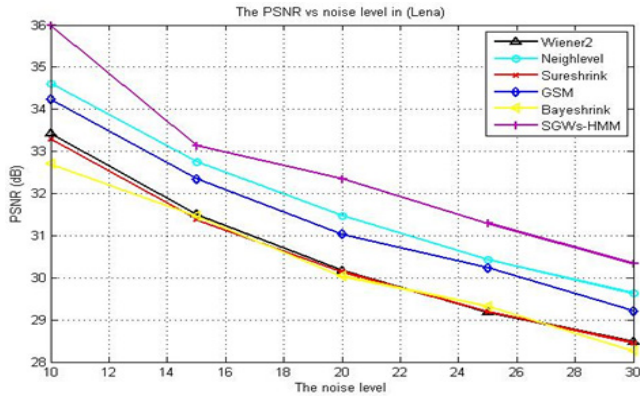


Figure 7. PSNR of Lena benchmark image.

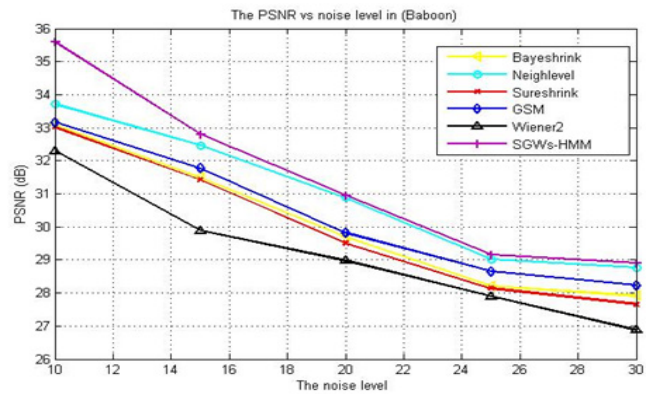


Figure 9. PSNR of Boat benchmark image.

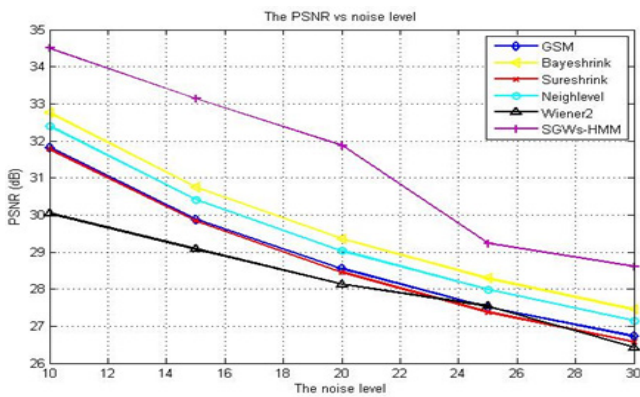


Figure 8. PSNR of Baboon benchmark image.

Figure 8 depicted that in noise of low levels of different algorithms the proposed techniques shows high quality images, but in the range of 15 to 18 noise levels, its performance degraded and becomes too close to the performance of NeighLevel. It is due to the complicated features of the baboon image that affected the image PSNR. BayeShrink filter shows worse results in this study as we can see it has 27 dB in high noise levels.

Finally, Figure 9 depicts the PSNR of benchmark image of Boat; the proposed method shows the highest PSNR compared to the rest of techniques under study. The proposed algorithm shows unique improvement in

Table 1. SSIM result of the denoised images by different algorithms at different noise levels

Methods	SureShrink	NeighLevel	BayesShrink	GSM	Wiener2 (5x5)	SGWs- HMM
Baboon						
$\sigma=10$	0.8721	0.8807	0.8661	0.8801	0.8592	0.9303
$\sigma=15$	0.8411	0.8511	0.8332	0.8419	0.7808	0.8899
$\sigma=20$	0.7718	0.8203	0.7614	0.7822	0.7523	0.8801
$\sigma=25$	0.7387	0.7574	0.7112	0.7332	0.7109	0.8565
$\sigma=30$	0.6802	0.7362	0.6419	0.6978	0.6714	0.8441
Lena						
$\sigma=10$	0.9252	0.9401	0.9144	0.9301	0.9296	0.9517
$\sigma=15$	0.9004	0.9170	0.8662	0.9102	0.9038	0.9202
$\sigma=20$	0.8699	0.8861	0.8418	0.8711	0.8655	0.8908
$\sigma=25$	0.8412	0.8712	0.8177	0.8697	0.8418	0.8702
$\sigma=30$	0.8214	0.8520	0.7896	0.8473	0.7995	0.8663
Boat						
$\sigma=10$	0.9107	0.9128	0.9001	0.9180	0.9123	0.9422
$\sigma=15$	0.8762	0.8914	0.8722	0.8802	0.8814	0.9012
$\sigma=20$	0.8587	0.8744	0.8573	0.8611	0.8554	0.8826
$\sigma=25$	0.8302	0.8519	0.8195	0.8400	0.8389	0.8644
$\sigma=30$	0.7900	0.8205	0.7812	0.8051	0.7987	0.8487

the range from 1 to 1.8 dB in comparison with BayeShrink and SureShrink. Although this kind of natural images has complicated features, our method performed well where it preserved the most of finer details. Furthermore, techniques like GSM and SureShrink shows close results to each other. Wiener2 considered as the poorest filter in this comparison where it shows the lowest PSNR values comparing with the rest methods.

In the qualitative assessment part of this study, Figure 10 depicted benchmark image of Baboon in comparison with several best state of the art denoising methods. From the first look to the figure, we can address the conclusion that the proposed techniques outperformed the rest of methods where it kept the main features of the noise-free image and also preserved the smooth area. The rest of denoising techniques showed poor quality image where they miscarried to keep the most important features of the original image. Not only showed low quality in the edge and ridges regions, but also in the flat areas of the reconstructed.

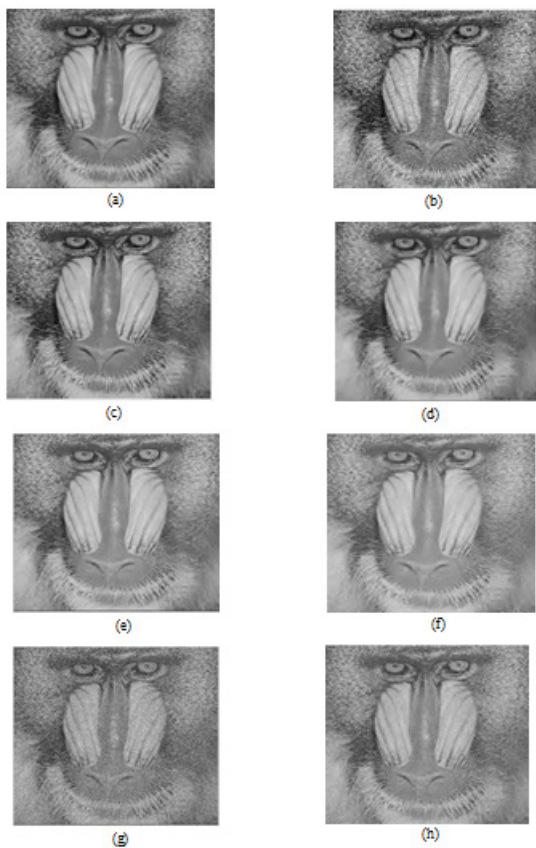


Figure 10. Results of Baboon image (512x512) with various denoising methods. (a) original image, (b) Noisy image($\sigma=25$) (c) Wiener2 filter (d) SureShrink (e) NeighLevel (f) GSM (g) BayesShrink (h) the proposed algorithm (SGWs-HMM).

Furthermore, the hardware components of the system are stated in this paper. In this regard, the tests and experiments were conducted a PC (CPU: Intel core i7 3.20 GHz, 4GB RAM). Figure 11 depicts the running time of different denoising algorithms which used in this study. In order to perform the whole denoising processes, SGWs-HMM takes around 128 Seconds in Baboon and around 100 to 128 Seconds for Lena and Boat benchmark images respectively.

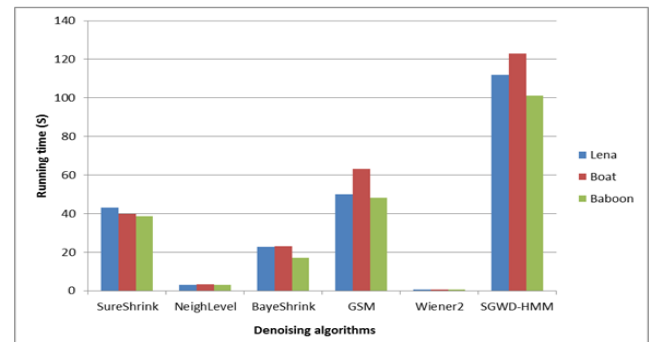


Figure 11. Execution time of the tested images with different denoising algorithms.image.

The computation complexity in the proposed algorithm is expensive because the algorithm always undergoes several denoising iterations to find out the coefficient's needs and the parameters of the thresholding method. However, Wiener2 reflects the short time period to execute its commands where it was around 1 second, whereas NeighLevel has in average 3.18 seconds. Finally, GSM and SureShrink have running time in range of 39 to 62 Seconds.

6. Conclusion

Image denoising algorithm has been proposed in this paper using second-generation wavelets and by utilizing the non-stationary feature of the noisy coefficients in the wavelet domain. In addition, the highly dependencies among the wavelet coefficients has been exploited perfectly by hidden Markov model. In this study, firstly, a deep survey of the state-of-the-art denoising techniques was described. Then, a new algorithm for image denoising is proposed, this algorithm exploits the features of the higher order statistical coupling between the adjacent discrete wavelet coefficients in the same neighbourhood with active translation-invariant in wavelet transforms. Furthermore, the main aim of the coefficient evaluation method using

HMM concept is principally its generalization. Finally, several comparisons among the state of the arts denoising algorithms are demonstrated and the performances are evaluated in terms of qualitative assessment by finding out the best reconstructed image and quantitatively using PSNR and SSIM validation methods. The result and discussion part shows the main results of this study where our algorithm outperformed the best state of art noise removal approaches. In the issue of the complexity of the proposed algorithm, SGWs-HMM is considered the slowest algorithm and less efficient among the algorithms under study due to its statistical structure and over-complete representation. This burden can be significantly prevented by reducing the variables in the structure of the algorithm and decreasing the statistical and logical processes which reduce the number of iterations in the algorithm.

7. References

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