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HYBRID IMAGE DENOISING USING WIENER FILTER WITH DISCRETE WAVELET TRANSFORM AND FRAMELET TRANSFORM

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ABSTRACT

Removal of noise from an image is an essential part of image processing systems. In this paper a hybrid denoising algorithm which combines spatial domain Wiener filter and thresholding function in the wavelet and framelet domain is done. In this work three algorithms are proposed. The first hybrid denoising algorithm using Wiener filter with 2-level discrete wavelet transform (DWT), the second algorithm its using Wiener filter with 2-level framelet transform (FLT) and the third hybrid denoising algorithm its combines wiener filter with 1-level wavelet transform then apply framelet transform on LL of wavelet transform. The Wiener filter is applied on the low frequency subband of the decomposed noisy image. This stage will tend to cancel or at least attenuate any residual low frequency noise component. Then thresholding detail high frequency subbands using thresholding function. This approach can be used for grayscale and color images. The simulation results show that the performance of the first proposed hybrid denoising algorithm with discrete wavelet transform (db5 type) is superior to that of the second and third proposed algorithms and to that of the conventional denoising approach at most of the test noisy image with Gaussian noise and Slat & pepper noise while the third proposed denoising algorithm with hybrid wavelet & framelet transform is superior to that of the other proposed algorithms at noisy images with speckle noise.

KEYWORDS

Wiener Filter, Discrete Wavelet Transform, Framelet Transform, Gaussian noise, Salt& pepper noise, Speckle noise, PSNR, RMSE

ازالة الضوضاء باستخدام تهجين مرشح وينر مع تحويل المويجة والتحويل الاطاري

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الخلاصة

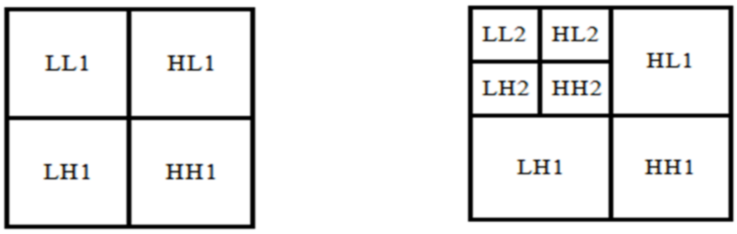
تعد عملية ازالة الضوضاء من الصور جزء مهم في معالجة الصور ولاهمية الصور في مجال الحياة ولكونها تتعرض عند التعامل معها او ارسالها عبر القناة للعديد من الضوضاء او التشويش لذا وجب استخدام طرق لتنقيتها من الضوضاء الداخله اليها. يقترح هذا البحث ثلاث نظريات بطرق مهجنة باستخدام مرشح وينر مع تحويل المويجة والتحويل الاطاري لازالة الضوضاء عن الصور الرمادية والصور الملونة. طبقت الطريقة الاولى بتهجين مرشح وينر مع تحويل المويجة على مجموعة من الصور المتعرضة لانواع من الضوضاء منها GAUSSIAN NOISE, SLAT & PEPPER NOISE AND SPECKLE NOISE وطبقت ايضا الطريقة الثانية بتهجين مرشح وينر مع التحويل الاطاري , وطبقت الطريقة الثالثة بتهجين مرشح وينر مع تحويل المويجة والتحويل الاطاري معا, ووضحت النتائج التجريبية ان الطريقة الاولى اعطت افضل نتائج مع الصور المتعرضة لضوضاء من نوعGAUSSIAN NOISE و SLAT & PEPPER NOISE بينما الطريقة الثالثة اعطت افضل نتائج بالنسبة للصور المتعرضة مع ضوضاء من نوع SPECKLE NOISE وتم مقارنة العمل ايضا مع طرق تقليدية ونظريات من اعمال اخرى و اعطت الطريقة الاولى والثالثة افضل النتائج.

1. INTRODUCTION

Image denoising restores the details of an image by removing unwanted noise. Digital images become noisy when these are acquired by a defective sensor or when these are transmitted through a noisy channel [1]. Noise may be classified as substitutive noise (impulsive noise: e.g., salt and pepper noise, random valued impulse noise, etc.), additive noise (e.g., additive white Gaussian noise) and multiplicative noise (e.g. speckle noise) [2]. However, in this paper the investigation has been done in salt & pepper noise, Gaussian noise and Speckle noise. In general, the goal of any noise removal scheme is to suppress noise as well as to preserve details and edges of image as much as possible. Many denoising methods have been proposed over the years, such as the Wiener filter, wavelet thresholding, anisotropic filtering, bilateral filtering, total variation method, and non-local methods. Among these, wavelet thresholding has been reported to be a highly successful method [3]. In wavelet thresholding a signal is decomposed into approximation (low-frequency) and detail (high-frequency) subbands, and the coefficients in the detail subbands are processed via hard or soft thresholding. The hard thresholding eliminates (sets to zero) coefficients that are smaller than a threshold; the soft thresholding shrinks the coefficients that are larger than the threshold as well. The main task of the wavelet thresholding is the selection of threshold value and the effect of denoising depends on the selected threshold: a bigger threshold will throw off the useful information and the noise components at the same time while a smaller threshold cannot eliminate the noise effectively. A major strength of the wavelet thresholding is the ability to treat different frequency components of an image separately; this is important, because noise in real scenarios may be frequency dependent. But, in wavelet thresholding the problem experienced is generally smoothening of edges [3]. In this work a hybrid denoising method is proposed to find the best possible solution, so that PSNR of the image after denoising is optimal. The proposed model is based on wavelet transform or/and framelet transform which has been successfully used in noise removal [4]and hybrid with Wiener filtering, which exploits the potential features of both wavelet transform and Wiener filter at the same time their limitations are overcome [3].

2. DISCRETE WAVELET TRANSFORM (DWT)

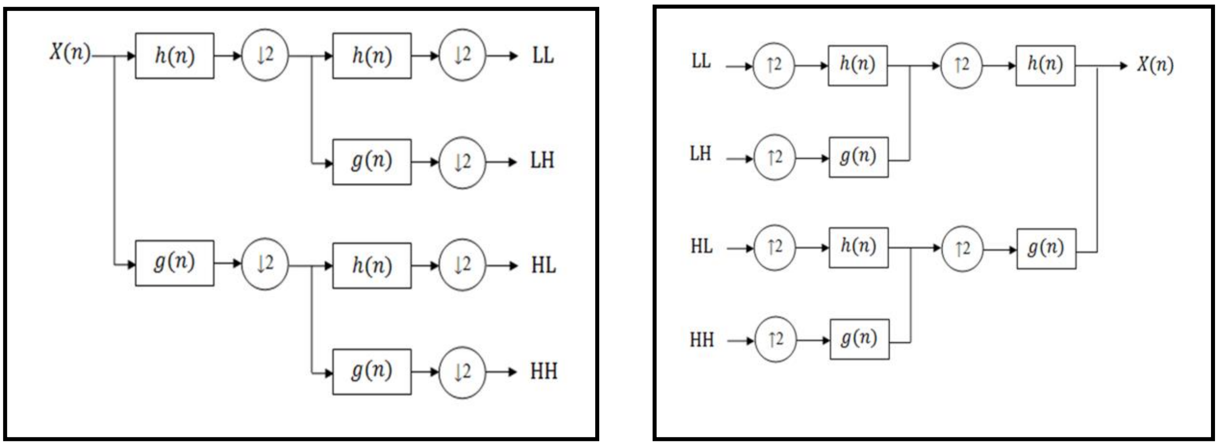
When DWT is applied to noisy image, image is divided into four sub bands as shown in Fig. 1(a).These sub bands are formed by separable applications of horizontal and vertical filters. Coefficients that are represented as sub bands LH1, HL1 and HH1 are detail images while coefficients are represented as sub band LL1 is approximation image. The LL1 sub band is further decomposed to obtain the next level of wavelet coefficients as shown in Fig. 1(b) [1].



(a) One level **(b) Two level**

Fig. 1. Decomposition DWT

Fig. 2 (a and b) show that the filter bank structure for 2D analysis DWT and 2D synthesis DWT, respectively.

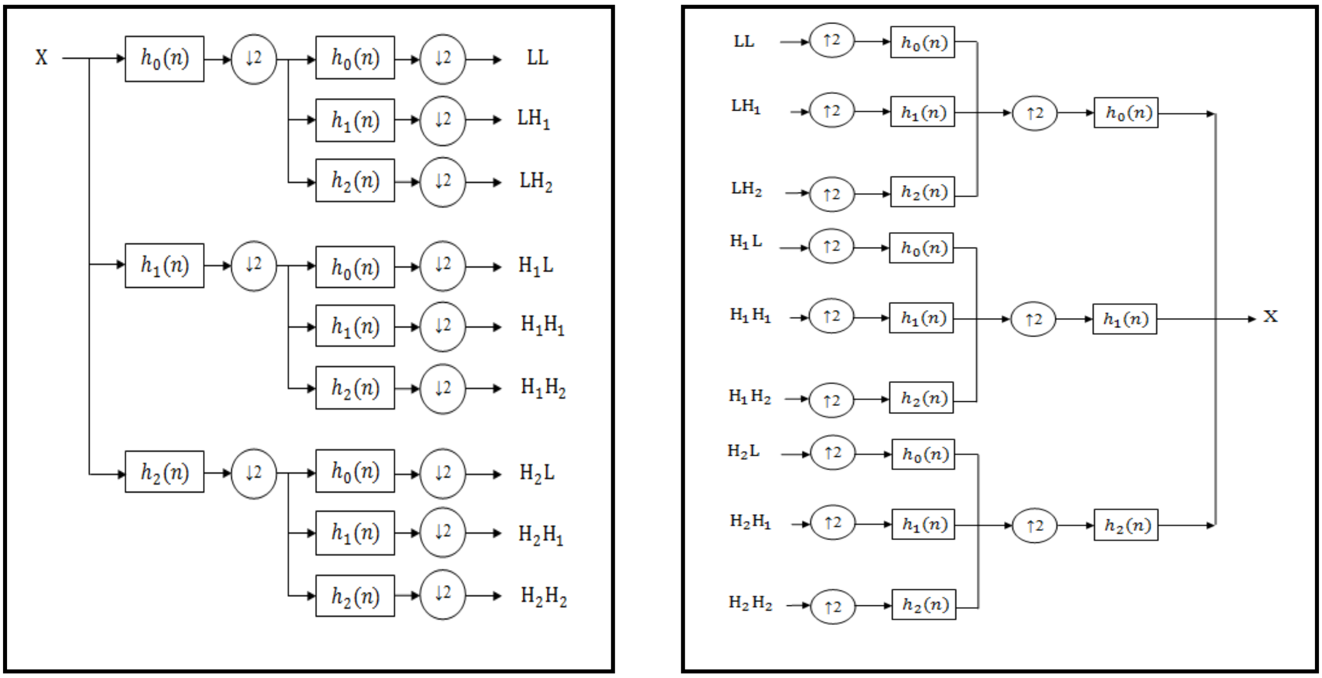


a. Synthesis **b. Analysis**

Fig. 2: Filter bank for 2D- DWT Analysis and Synthesis [5]

3. FRAMELET TRANSFORM (FLT)

The three-channel filter bank, which is used to develop the FLT corresponding to a wavelet frame, Fig. 3 (a and b) show that the filter bank structure for 2D analysis FT and 2D synthesis FT, respectively.



a. Analysis **b. Synthesis**

Fig. 3: Analysis and synthesis Stages of a 2-D Single Level FLT [4]

4. WIENER FILTER

Wiener theory, formulated by Norbert Wiener, forms the foundation of data-dependent linear least square error filters. Wiener filters play a central role in a wide range of applications such as linear prediction, echo cancellation, signal restoration, channel equalization, time-delay estimation and additive noise reduction [6]. In this paper, the purpose of the Wiener filter is to filter out the noise that has corrupted a signal. This filter is based on a statistical approach.

Mostly all the filters are designed for a desired frequency response. Wiener filter deals with the filtering of an image from a different view. The goal of wiener filter is reduced the mean square error as much as possible [2]. Consider a signal x (m) observed in a broadband additive noise n (m) and model as [6]:

$$y(m) = x(m) + n(m) \quad (1)$$

Assuming that the signal and the noise are uncorrelated, it follows that the autocorrelation matrix of the noisy signal is the sum of the autocorrelation matrix of the signal x (m) and the noise n(m):

$$R_{yy} = R_{xx} + R_{nn} \quad (2)$$

And we can also write

$$r_{xy} = r_{xx} \quad (3)$$

Where R_{yy}, R_{xx} and R_{nn} are the autocorrelation matrices of the noisy signal, the noise-free signal and the noise respectively, and r_{xy} is the cross correlation vector of the noisy signal and the noise-free signal. Substitution of eq. 2 & 3 in the Wiener filter Equation ($W = R_{yy}^{-1}\, r_{xy}$), yields [6]:

$$W = (R_{xx} + R_{nn})^{-1} r_{xx} \quad (4)$$

Eq. 4 is the optimal linear filter for the removal of additive noise. In the following, a study of the frequency response of the Wiener filter provides useful insight into the operation of the Wiener filter. In the frequency domain, the noisy signal Y(f) is given by

$$Y(f) = X(f) + N(f) \quad (5)$$

Where X(f) and N(f) are the signal and noise spectra respectively. For a signal observed in additive random noise, the frequency-domain Wiener filter is obtained as

$$W(f) = \frac{P_{XX}(f)}{P_{XX}(f) + P_{NN}(f)} \quad (6)$$

Where $P_{XX}(f)$ and $P_{NN}(f)$ are the signal and noise power spectra respectively. Dividing the numerator and the denominator of eq. 6 by the noise power spectra $P_{NN}(f)$ and substituting the variable $SNR(f) = P_{XX}(f)/P_{NN}(f)$ yields

$$W(f) = \frac{SNR(f)}{SNR(f) + 1} \quad (7)$$

Where SNR is a signal-to-noise ratio.

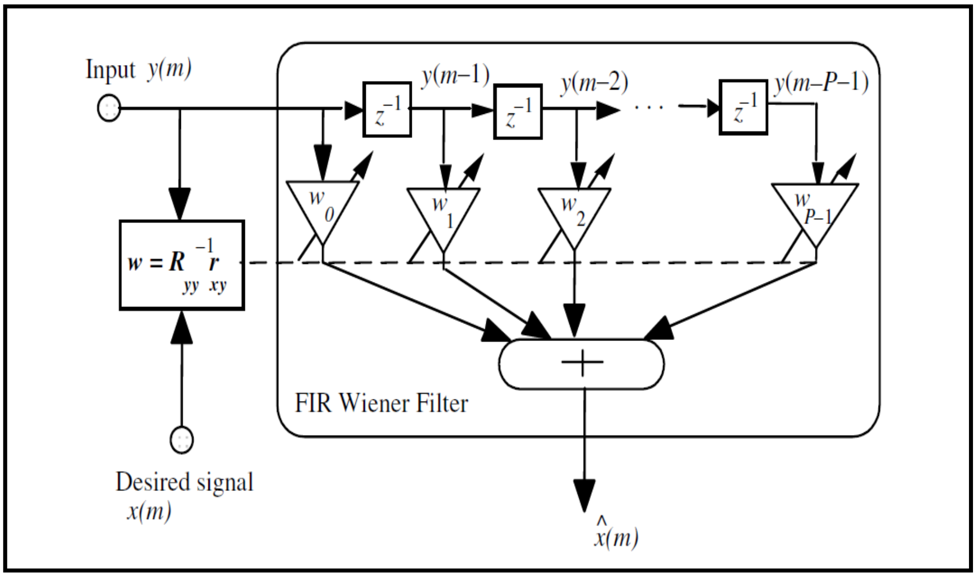


Fig. 4: Illustration of a Wiener filters structure [6]

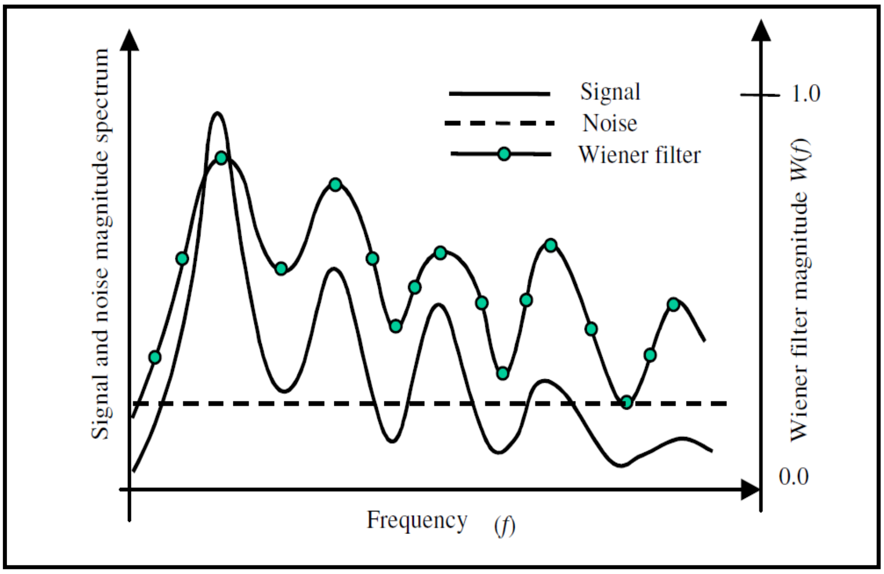


Fig. 5. Illustration of the variation of Wiener frequency response with signal spectrum for additive white noise. The Wiener filter response broadly follows the signal spectrum [6]

5. PROPOSED ALGORITHM

In this work state three algorithms. Fig. 6 shows the flow chart of these algorithms:

In the first proposal, 2-Level wavelet decomposition is applied on the noisy image, in the second proposal, 2-Level framelet transform is applied on the noisy image and in the third proposal, 1-Level wavelet transform then 1-Level framelet transform is applied on the noisy image. Then apply wiener filter for low frequency domain and soft thresholding for high frequency domains. The filtered decomposed image is reconstructed by applying inverse wavelet transform and inverse framelet transform to get the denoised image.

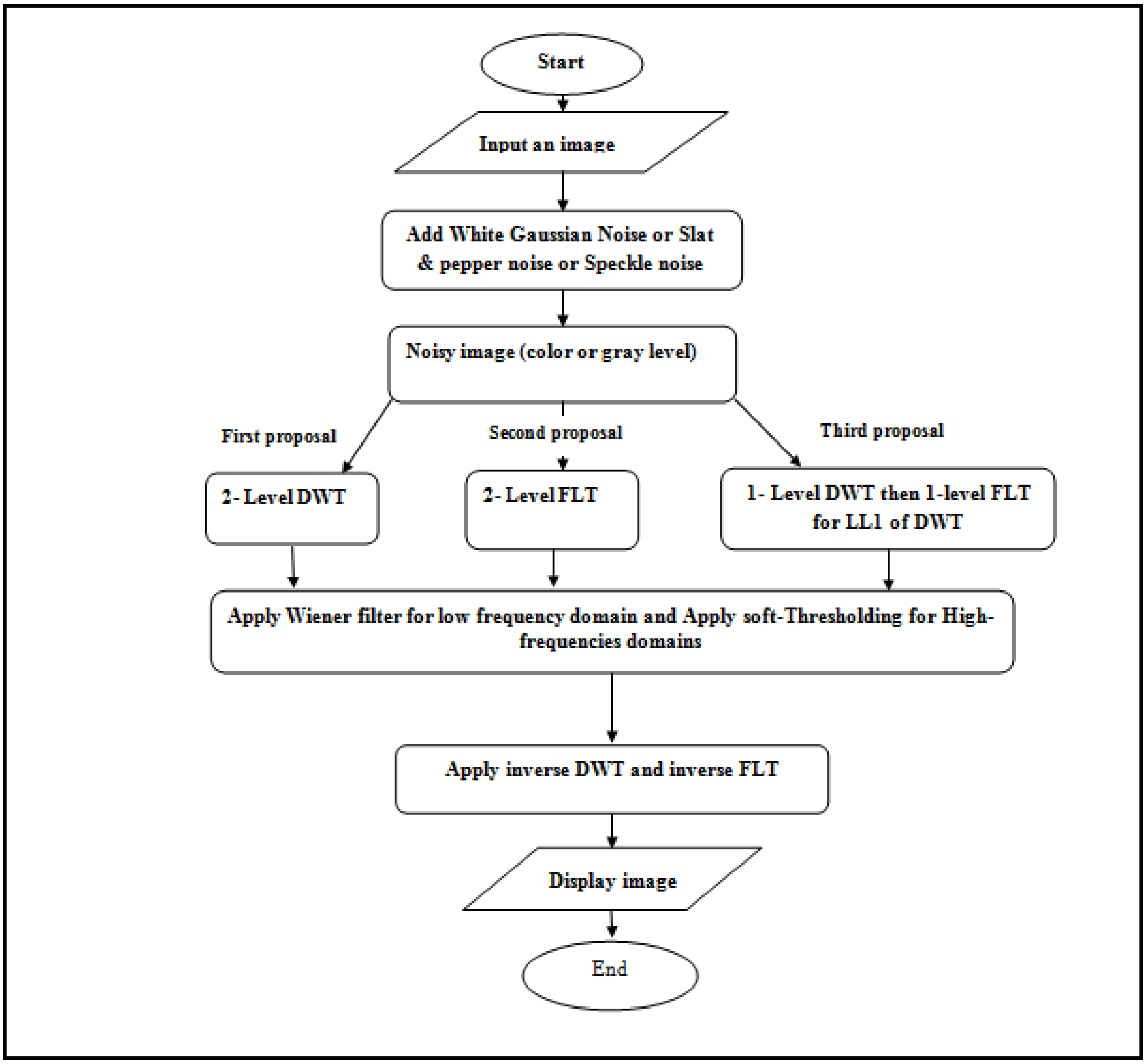


Fig. 6. Flow chart of proposed algorithm

6. RESULTS AND DISCUSSION

Fig. 7 shown denoising some grayscale images with proposed algorithm 1 and the results in Tables 1, 2 & 3 shown the performance of PSNR and MSE compared with other algorithms. Table (1) illustrates that the PSNR and RMSE for Dog.jpg image using DWT (db5) is better than different algorithms.

Table (2) illustrates that the proposed algorithm using wavelet & framelet transform for Lena image gives the best results.

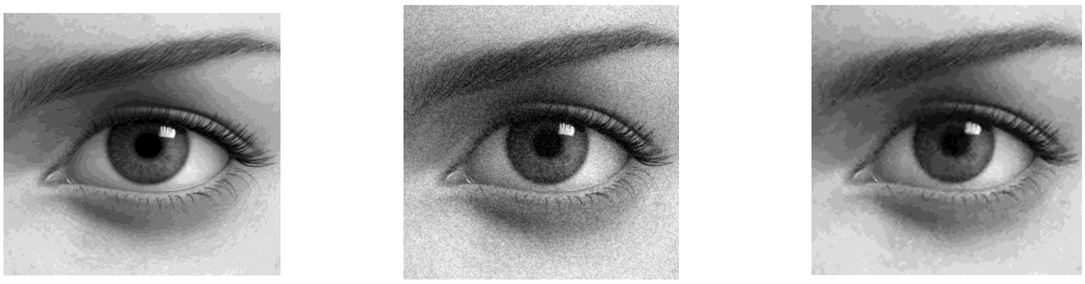
Table (3) illustrates the results of testing the proposed algorithm (1) compared with algorithm (2 and 3) on different grayscale images.

a. Original image b. Noisy image c. Denoised image

Image (1) :Dog.jpg

a. Original image b. Noisy image c. Denoised image

Image (2): cameraman.tif



a. Original image b. Noisy image c. Denoised image

Image (3):eye.bmp

a. Original image b. Noisy image c. Denoised image

Image (4)

a. Original image b. Noisy image c. Denoised image

Image (5)

Fig. 7. Denoising some images with 0.01 noise variance taking additive white Gaussian noise in proposed algorithm 1

Table 1. Performance comparison between proposed algorithms at Dog.jpg image with 0.01 noise variance taking additive white Gaussian noise

Algorithm	RMSE	PSNR
Proposed algorithm 1 using discrete wavelet transform (db1)	12.535	26.1682
Proposed algorithm 1 using discrete wavelet transform (db3)	10.1951	27.9629
Proposed algorithm 1 using discrete wavelet transform (db5)	9.537	28.5420
Proposed algorithm 2 using framelet transform	14.510	24.897
Proposed algorithm 3 using wavelet & framelet transform	13.519	25.5119

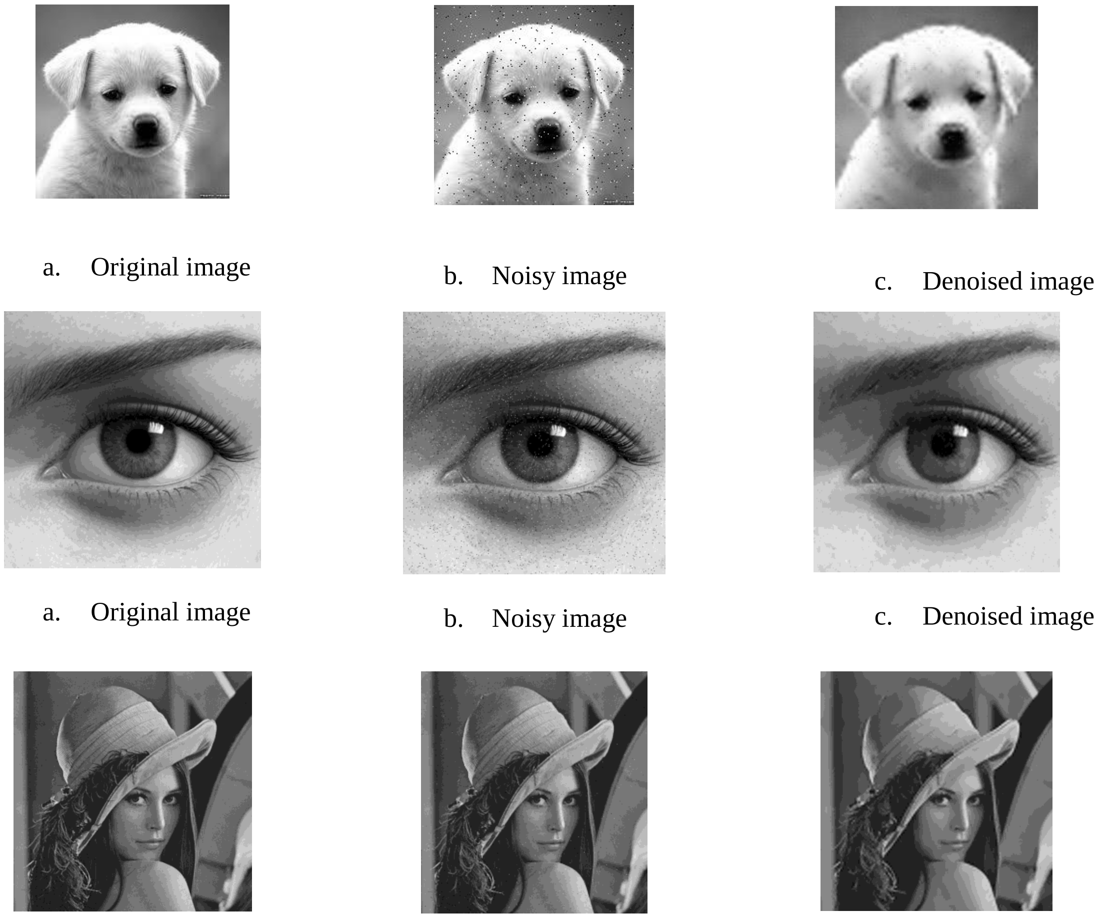
Table 2. Performance comparison between proposed algorithms at Lena image with 0.001 noise variance taking additive white Gaussian noise

Algorithm	PSNR	MSE
Proposed algorithm 1 using discrete wavelet transform (db5)	29.3812	66.9759
Proposed algorithm 2 using framelet transform	26.6492	125.6360
Proposed algorithm 3 using wavelet &framelet transform	31.8511	37.9251

Table 3. PSNR and MSE for some grayscale images in proposed algorithms with 0.01 noise variance taking additive white Gaussian noise

Image	Proposed algorithm 1 using discrete wavelet transform		Proposed algorithm 2 using framelet transform		Proposed algorithm 3 using DWT & FLT transform	
	PSNR	MSE	PSNR	MSE	PSNR	MSE
Image 2	23.3124	298.5356	22.3169	375.4511	23.8886	261.4480
Image 3	30.0151	63.7871	28.9553	81.4172	25.5999	176.2976
Image 4	26.4611	131.1981	24.6067	201.0778	25.5918	201.7705

Fig. 8 shows denoising some grayscale images with noisy image by Slat & Pepper noise and the results of PSNR shown in Table 4.



a. Original image b. Noisy image c. Denoised image

a. Original image b. Noisy image c. Denoised image

a. Original image b. Noisy image c. Denoised image

Fig. 8. Denoising some images with slat & pepper noise in proposed algorithm

Table 4. Performance comparison between proposed algorithms at Lena image with slat & pepper noise

Algorithm	PSNR	MSE
Proposed algorithm 1 using discrete wavelet transform (db5)	29.5350	64.6449
Proposed algorithm 2 using framelet transform	26.6932	124.3694
Proposed algorithm 3 using wavelet &framelet transform	29.0750	71.8675

Table 5. PSNR and MSE for some grayscale images in proposed algorithm 3 with Speckle noise

Image	Proposed algorithm 1 using discrete wavelet transform		Proposed algorithm 2 using framelet transform		Proposed algorithm 3 using DWT & FLT transform	
	PSNR	MSE	PSNR	MSE	PSNR	MSE
Image 2	23.6961	273.2955	22.6652	346.5134	26.3474	148.4231
Image 3	31.5838	44.4492	30.1229	62.2234	29.5610	70.8168
Image 4	27.4267	105.0414	25.1097	179.0868	29.1372	70.8450

Fig. 9 shows denoising some color images with noisy image by Gaussian noise and the results of PSNR shown in Table 6.



(a) Original image (b) Noisy image (c) Denoised image



(a) Original image (b) Noisy image (c) Denoised image



(a) Original image (b) Noisy image (c) Denoised imag

Fig. 9. Denoising Dog and Flower color images with 0.01 noise variance taking additive white Gaussian noise in proposed algorithm

Table 6. PSNR and MSE for some color images in proposed algorithms with 0.01 noise variance taking additive white Gaussian noise

image	Proposed algorithm 1 using discrete wavelet transform		Proposed algorithm 2 using framelet transform		Proposed algorithm 3 using framelet transform	
	PSNR	MSE	PSNR	MSE	PSNR	MSE
Dog	28.4334	93.2693	23.7560	273.8291	25.6804	175.8100
Flower	27.0444	128.4209	26.9514	131.2022	25.4611	184.9125
Lena	27.7618	108.8690	25.9402	165.5984	25.2636	193.5187

Fig.10 shows denoising some color images with noisy image by Slat & Pepper noise and the results of PSNR shown in Table 7.

(a) Original image

(b) Noisy image

(c) Denoised image

(a) Original image

(b) Noisy image

(c) Denoised image

(a) Original image

(b) Noisy image

(c) Denoised image

Fig. 10. Denoising Dog and Flower color images with Slat & Pepper noise in proposed algorithm

Table 7. PSNR and MSE for some color images in proposed algorithms with slat & pepper noise

image	Proposed algorithm 2 using FLT		Proposed algorithm 1 using DWT (db1)		Proposed algorithm 1 using DWT (db5)		Proposed algorithm 3 using DWT (db5) & FLT	
	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
Flower	29.0402	73.5540	27.8492	106.6986	29.4647	81.1079	28.3295	95.5286
Dog	24.2102	246.6396	26.9556	131.0759	30.3571	59.8928	29.6168	71.0233
Lena	26.3245	151.5744	27.3761	118.9789	28.7638	86.4369	29.0383	81.1434

Tables 1-7 illustrates that the performance of the first proposed hybrid denoising algorithm with discrete wavelet transform (db5 type) and the third proposed denoising algorithm with hybrid wavelet & framelet transform is superior to that of the second proposed algorithm and to that of the conventional denoising approach at noisy image with Gaussian noise, Slat & Pepper noise and Speckle noise. Some of these results that the PSNR for Lena image in proposed method with Gaussian noise is 31.8511, while in another algorithms such as ALPHA is 25.144, MAX is 25.6988 and MINMAX is 28.4067 [7]. And the PSNR for Dog image in proposed method with Gaussian noise is 28.5420, while the PSNR is 27.927 using Fuzzy filter in wavelet domain [2]. And the PSNR for Lena image in proposed method with Slat & Pepper noise is 29.5350, while in another algorithms such as ALPHA is 25.3335 , MAX is 27.7995 [7].

7. CONCLUTION

Based on the experiments performed in this work, it can be concluded that the denoising methods depending on noise types, where the results illustrates that the proposed algorithm 1 is the best amongst three in terms of PSNR and MSE, in addition to be more uniform and consistent in most the types of images tested with Gaussian noise and slat & pepper noise while the proposed algorithm 3 illustrates that the Hybrid filter is able to recover much more detail of the original image and provides a successful way of image denoising with speckle noise

8. REFERENCE

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