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Image denoising using wavelet and median filter based on raspberry Pi

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ABSTRACT

The goal of any de-noising technique is to remove noise from an image which is the first step in any image processing. The noise removal method should be applied watchful manner otherwise artefacts can be introduced which may blur the image. In this work, three levels of Gaussian noise are used for adding noise on the original image (σ=10, σ=50, σ=100) and also (σ=15, σ=20, σ=25) to compare with *Ramadhan et al.* [1] and analysis with it to test embedded system with median filter. Performance evaluation of the median filter, wavelet threshold de-noising techniques is provided. The techniques used are namely the median filter and wavelet threshold is used to remove noise based on raspberry pi with Python. Four methods to remove noise image are used. MF, WT, MF before and after WT. The results showed the image of camera was better than other after tested all the methods with Gaussian noise σ=10. On other hand the other images were better than image of camera for the Gaussian level 50 and 100. The results were good in median filter in wavelet threshold based on Raspberry Pi, which is compared with overall result most of images butter in median filter.

KEYWORDS
Image Denoising
Median Filter
Wavelet Threshold
Gaussian Noise

1. Introduction

Digital image processing is known as a process which uses algorithm on digital image. It is one of the digital signal processing areas. It can bring some advantages as following: Many algorithms are applied to the input data, remove noise and signal distortion during processing.

There are a wide range of techniques used for image processing. These techniques developed in the 1960's and were mainly used for applications of wire photo, medical image and character recognition. However, these techniques were very costly and were seen as a disadvantage. Then in 1970s, cheaper means in the form of computers and dedicated hardware became available. Images were processed in real time and the only limitation detected was television standards conversion. Finally, in the 2000's, the discoveries of speedy generation of computers and signal processors, it helped digital image processing to become the most common form of image processing mainly. Because, it is not only the most multilateral method, but also the most inexpensive [2], [3]. More methods were eventually introduced. For instance, [4] proposed a new method of calculating the phase congruency through the use of wavelets. 1D signal is extended to allow the calculation of phase congruency in 2D images. High pass filter is used to obtain image information at different scales. On the other hand, the reseachers [5] introduced a new Bayesian image de-noising technique with two complementary discontinuity measures. The spatial-gradient, and the other which is a continuity measure detects contextual discontinuities for feature preservation as shown in his findings whereby a clear high peak signal to noise ratio (PSNR) is gained from noisy images, and the noise is successfully decreased while preserving edge components. Till now, most methods have exhibited limitations namely high costs, complexity, and blurring image losing details. Therefore, this study proposes an image de-noising in wavelet and spatial domain to overcome these limitations. Local mean filter, median filter, and wavelet threshold are tended to remove noise using de-noising image in wavelet and spatial domain.

This research devided in severap part. Section II explain the m methodology includes Literature Review, addition noise model, spatial domain filtering, Wavelet transform, Wavelet threshold, and the parameters. The results willo be delivered in Section III, includes Image Denoising, comparison benchmark. The last section (IV) shows the conclusion.

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2. Method

2.1. Literature Review

In [6], adaptive wavalet thresholding is proposed to improve PSNR. thresholding denoising in wavelet domain adaptive Wiener filter is introduced by [7]. *Also, Anupama et al* [8] Emerging wavelet domain Denoising methods such as soft and hard thresholding, bayeshrink, visushrink and SUREshrink to improve PSNR In addition, Hussain et al [9] proposed Gaussian, Bilateral filter, Bayes Shrink, SURENeighShrink. Table 1 shows an overview of image denoising.

Table 1. Summarize of Literature Review

Ref. No	Method OR Technique	Value of PNSR & MSE
[6]	adaptive wavelet thresholding	MSE=24.9
[10]	thresholding denoising in wavelet domain adaptive Wiener filter	PSNR 30.76 MSE=54.57
[8]	Emerging wavelet domain Denoising methods such as soft and hard thresholding, bayeshrink, visushrink and SUREshrink	PSNR = 37.529605 MSE=11.484705
[9]	(Gaussian , Bilateral filter, Bayes Shrink, SURENeighShrink)	PSNR =30.910
[11]	wavelet domain based on the generalized Guassian distribution (GGD), NormalShrink	PSNR =4%
[12]	(Bayes Shrink, Sure shrink, Bivariate shrink, Block Shrink)	PSNR =68.59
[13]	Non-local means filters and its method noise thresholding using wavelets	PSNR =35.60
[14]	Hard thresholding + median filter	PSNR=34.07, MSE=21.22
[15]	Mf	PSNR= 74.2921, MSE= 0.0024
[16]	spatial domain BF and hybrid thresholding function in the wavelet domain	PSNR=23.5499 MSE=23.0438
[17]	mean filter +WT	PSNR=26.6476
[18]	satellite image enhancement system consisting of denoising and resolution enhancement	PSNR=33.09
[19]	WT, BF, GF and BFWT	PSNR=34.76
[1]	MF + DWT	PSNR=26.5469

2.2. Additive Noise Model

A corrupted noisy signal is produced by adding the original signal and Noise, and called as additive noise and model as demonstrated in (1) [13].

$$W(x,y) = s(x,y) + n(x,y) \tag{1}$$

Where, s(x,y) indicates to the original image intensity, while n(x,y) represents the noise to produce the noisy signal w(x,y) at (x,y) pixel position [13], [20]. Fig. 1 shows the example of Gaussian noise [15] .

Fig. 1. (a) Original and (b) Gaussian noise image

2.3. Spatial domain filtering

This method represented as a conventional method. By the using spatial filters, the noise from the digital images can be eliminated. It is categorized into two categories: linear and nonlinear filters [7].

Median filtering can be identified as a nonlinear method that apply to remove noise from images. It is commonly used for its good and effective results at eliminating noise while preserving edges [21], [13].

Reseachers [22] state that the median filter uses 3×3, 5×5 or 7×7 window as following the moving window principle. The center pixel value of the window will be exchanged with the calculated value of median.

2.4. Wavelet Transforms

For more than a century ago, the concept of wavelet was concealed in the works of mathematicians. In 1873, Karl Weirstrass described how a family of functions can be made by superimposing scaled versions of a given basis function in a mathematic way. Describing the disturbances that regenerate and proceed outwardly from a sharp seismic impulse was the origins of using the term wavelet in the field of seismology. The meaning of wavelet is a “small wave”. Where it reflects the condition that the window function is limited length compactly maintained. While the wave is a periodic which indicated to an oscillating function of time or space. In contrast, wavelets considered to be localized waves. Add on, wavelets are suitable to analysis of transient signals. As well as, they have their energy centered in time[23], [24].

The signal in wavelet analysis needs to be analysed through multiplication with wavelet function. Follow that a comparison for each transform segment produced. There are two types of results, if the result brings good time resolution and poor frequency resolution, it means that the Wavelet Transform at high frequencies. while the Wavelet Transform will be at low frequencies only if the Wavelet Transform gives good frequency resolution and poor time resolution [23].

Wavelets have the ability to give spatial frequency information and forms as the key reason for this investigation. This property brings the opportunity for an improved discrimination between the noise and the data. The blurring effect or even overcome it can be completely reduced by the successful exploitation of wavelet transform. There are mainly two kinds of wavelet transform namely Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) [25].

According to [25], DWT of image signals provides improved spatial as a non-redundant image representation. Gaussian and Laplacian pyramid can be considered as an improvement represented example in the spectral localization of image formation compared to other multi scale representation. The study added that the DWT can be understood as signal decomposition in a set of independent spatially oriented frequency channels. Approximation and details are two signals that emerges and filtered through the pass of signal S. This process is known as decomposition or analysis. The components have the ability of going back into the original signal without the effect on the information. This procedure is well known as reconstruction or synthesis.

Reseachers [25] define the CWT as an application of the wavelet transform using an arbitrary scales and almost arbitrary wavelets. From the data obtained, there was a high correlated developmental transformation when non-orthogonal wavelets are used. CWT works by computing a convolution of the signal with the scaled wavelet.

2.5. Wavelet Threshold

In wavelet, coefficients with small absolute value are subjugated by noise. On the other hand, signal information can be carried more than noise only if the coefficients have large absolute value. a reconstruction that has lesser noise might be given when exchanging noisy coefficients (small coefficient below a certain threshold value) by zero and an inverse wavelet transform. The idea of thresholding was motivated created by the following assumptions made by [23] and listed below:

- Noise is spread out equally along all coefficients.
- The de correlating property of a wavelet transform creates a sparse signal most untouched coefficient is zero or close to zero.
- The noise level is not too high so that the signal wavelet coefficients can be distinguished from the noisy ones.

This process is well known as a simple and effective for noise decrease. Further, inserting zeros creates more scarcity in the wavelet domain.

There are two thresholding approaches are used frequently, namely Soft thresholding and Hard thresholding method [14], [23]. Soft thresholding function D(U,I) is called shrinkage function as well. As it takes the argument and shrinks the coefficient towards zero by the threshold U Thresholding operator is defined by equation (2). Hard thresholding operator is defined by equation (3).

$$D(U, I) = sgn(u)max(0, |u| - I) \tag{2}$$

$$\mathrm{D(U,I)} = \begin{Bmatrix} U & for \quad all\ |U| > \lambda \\ 0 & otherwise \end{Bmatrix} \tag{3}$$

For a better understanding of the way wavelets are work, a simple example will be shown. Using four pixels 1D image resolution, having values [9 7 3 5]. In order to compute the wavelet transform, Haar wavelet

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will be used to represent the selected image. Applying this will need to calculate the average and the pixels as the first step. Followed by using these pixel values [8 4] to get the new lower resolution image. By this level, losing some of the information is anticipated in this averaging process. To recover the original four-pixel values from the two averaged values, some of the detail coefficients need to be stored. Here 1 is chosen for the first detail coefficient, since the average computed is 1 less than 9 and 1 more than 7. However, in order to recover the first two pixels of the original four-pixel image, this single number is need to be used. Similarly, the second detail coefficient is -1, since 4 + (-1) = 3 and 4 - (-1) =5. Therefore, a lower resolution (two-pixel) version and a pair of detail coefficient can be found in the original image [24]. A full decomposition will be giving by repeating this method recursively on the averages as shown in Table 2.

Table 2. Decomposition to lower resolution

Resolution	Averages	Detail Coefficients
4	[9 7 3 5]	
2	[8 4]	[1 -1]
1	[6]	[2]

Therefore, the wavelet transform of the original four-pixel image is given by [6 2 1 - 1], for the 1D Haar basis. The technique used to calculate the wavelet transform by recursively averaging and differencing coefficients, can be called as filter bank. The image can be reconstructed to any resolution by recursively adding and subtracting the detail coefficients from the lower resolution versions.

The mother wavelet function ψ(t) for the Haar wavelet is described below:

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2 \\ -1 & \frac{1}{2} \le t < 1 \\ 0 & otherwise \end{cases}$$

While it's scaling function φ(t) is as follows:

$$\phi(t) = \begin{cases} 1 & 0 \le t < 1 \\ 0 & otherwise \end{cases}$$

Wavelets are known as mathematical functions that were settled by a group of scientists from numerous different scops just for sorting data by frequency. Followed by, translating these data by sorting theme using a resolution which matches its scale. In order to develop more complete pictures, further study of data at different levels are required. Since these features are studied separately, the two of small and large features are discernable. the wavelet transform is not Fourier-based which makes it different from the discrete cosine transform. This will assist that wavelets do a better job of handling discontinuities in data.

The Haar wavelet mechanism on data works through calculating the sums and differences of adjacent elements. Firstly, it runs on adjacent horizontal elements and then on adjacent vertical elements by using (4).

$$\frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \tag{4}$$

2.4. Parameters

In this study, two parameters are used, namely, MSE and PSNR. The calculation should be of high value to approximate the original image, as the (5) and (6) [26], [27].

$$MSE = \frac{1}{M.N}\sum_{i=0}^{M-1}\sum_{J=0}^{N-1}[F(i,j) - I(i,j)]^2 \tag{5}$$

$$PSNR = 10\,.\,log\left[\frac{max^2}{MSE}\right] \tag{6}$$

Where: I(i,j) original image , F(i,j) De-noising image

M and N is the size of the original image

Max: maximum pixel value of grayscale image that is used in this work which equals to 255.

2.5. Research Design and the Flowchart (Proposal)

Local median filter in wavelet threshold have many advantages, such as improving the quality of the image, reducing blurring of the image and, minimizing the cost. The input of an original image, whereby four images are used namely, Lena, pepper, Barbara, and camera man. The addition of Gaussian, salt and pepper are to obtain a Noisy image. Wavelet threshold and median filter on the other hand are used to remove noise by applying the calculations of two equations for PSNR and MSE.

The image is used as an input and is converted into codes once loaded using Raspberry Pi. The Gaussian noise is inserted by using a stated the equation. The image is further converted into another series codes after the addition of noise. This results in the production of a Noisy image as shown in Fig. 2. There are two steps to denoise image as the following:

1-Noisy image is added into a Local Median Filter as input to process the noisy image in order to locate and identify the MSE and PSNR. This is illustrated using the following equation where by the equation represents noising image (7).

$$w(x,y) = s(x,y) + n(x,y) \tag{7}$$

3-Comparison of the PSNR is done between the first and second step. A high PSNR count indicates good results while the final image is an approximation to the original image. Fig. 2 shows the proposal for image denoising only with median filter after adding Gaussian noise and getting PSNR. Fig. 3 shows the proposal for image denoising only with wavelet threshold after adding Gaussian noise and getting PSNR.

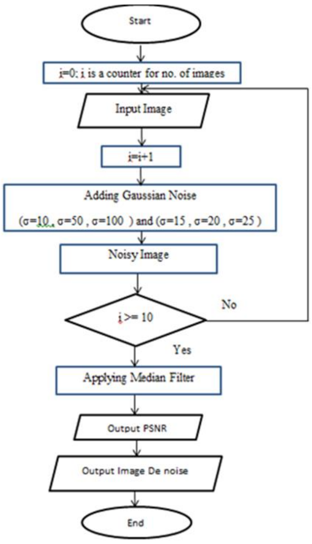

Fig. 2. Flowchart of Image Denoising Median Filter

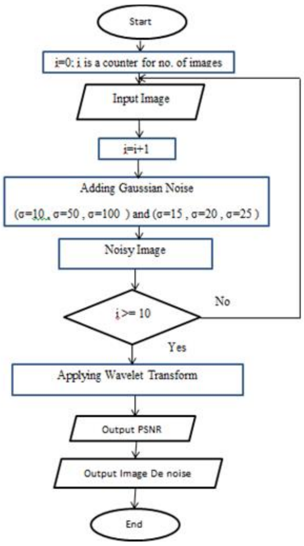

Fig. 3. Flowchart of Image Denoising Wavelet threshold

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Results and discussion

In this section, image denoising using median filter and wavelet threshold are considered. Where, PSNR in median filter and wavelet threshold has been evaluated. Ten Grayscale images sized 256×256 pixels each were used to reduce noisy images they are (Lena, Camera, Barbara, Actor, Pepper, Boat, Mandrill, Sail, Boy and Arctic hare) as shown in Fig. 4. Also, the effect of noise with different values of Sigma is used. The noise is additive Gaussian noise (AGN) for three values σ = 10, σ =50, and σ =100. Also, other three levels of noise are used σ = 15, σ =20, and σ =25 to compare with [1] using Median filter.

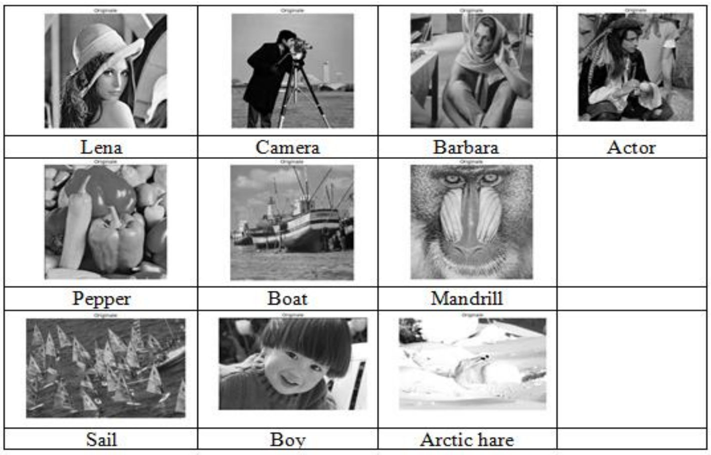

Fig. 4. Ten Original Images[1][19]

3.1. Image denoising

In this section median filter is implemented on various levels of noise and images. Fig. 5 shows the original image and Gaussian noisy image for three levels of noise (σ =10, σ = 50, and σ = 100)

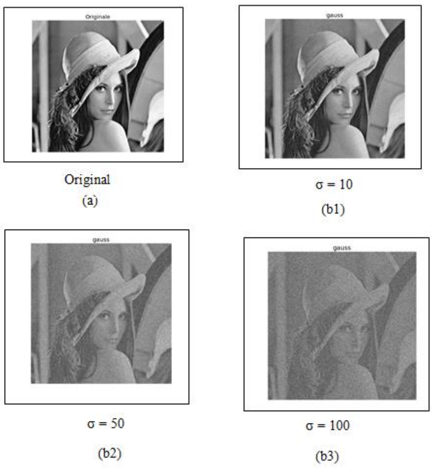

Fig. 5. Different between (a) the original image (b1,b2,b3) Gaussian noise image for three levels (σ=10, σ=50, σ=100)

Table 3 and Table 4 show the PSNR values with applying Gaussian noise at various noise levels and filtering with median, wavelet, median before and after wavelet threshold. It is clear that the best values of PSNR is for camera man, which it was 36.9705523 in median filter, 45.4153470 in Wavelet threshold, 36.266871 median before wavelet, and 35.9717183 median after wavelet. For the sigma = 10. While for the sigma = 50, and 100 the best values of PSNR is for Lena, which it was 24.5153459 in median filter, 20.4376083 in Wavelet threshold, 20.2790486 median before wavelet, and 20.4987449 median after wavelet. In contrast, the PSNR for Camera is 21.5869965 in median filter, PSNR=18.4833247 in Wavelet Threshold, PSNR=20.2790486 in median before threshold, and 18.4833247 in median after threshold. So, the best values of PSNR when sigma=50 and 100 were for Lena and other images for median filter, wavelet threshold, median before and after wavelet.

Table 3. PSNR values for median filter, and threshold, with different noise levels and time in Second

Image	Gaussian Noise ration	PSNR in (dB)	
		MF	WT
Lena	10	30.1341671	25.8543224
	50	24.5153459	20.4376083
	100	19.6866849	18.4515992
Barbara	10	23.057967	23.2151144
	50	21.4757781	19.2687872
	100	18.4215720	17.6596623
Camera	10	36.9705523	45.4153470
	50	21.5869965	18.4833247
	100	18.3482303	16.8155920
Pepper	10	28.4054283	24.0032192
	50	23.0051279	17.683284
	100	18.9297436	15.9668177
Boat	10	26.9328628	24.6380526
	50	23.2626507	19.8962057
	100	19.1875844	18.2781871
Mandrill	10	24.5070625	22.5542500
	50	22.1108869	19.4027530
	100	18.7221161	18.3452519
Sail	10	24.8482394	22.8471234
	50	22.2085110	18.9951028
	100	18.7399177	17.777237
Boy	10	26.3357341	24.4471915
	50	23.1972873	20.3629288
	100	19.1851968	18.3877155
Arctic hare	10	33.9343995	28.1693115
	50	25.4542918	22.2404697
	100	20.0151541	20.0670742
Actor	10	28.2386886	24.7536783
	50	23.7724344	19.9902071
	100	19.4320209	18.2058994

Table 4. PSNR values for median filter before and after wavelet threshold with different noise levels and time in Second

Image	Gaussian Noise ration	PSNR in (dB)	
		MF before WT	MF after WT
Lena	10	25.025659	25.8820582
	50	20.2790486	20.4987449
	100	18.3880113	18.4688057
Barbara	10	22.1631683	22.4110454
	50	19.1540847	19.2956461
	100	17.5989055	17.6664083
Camera	10	35.9717183	36.266871
	50	18.2070798	18.5380349
	100	16.7043304	16.8427152
Pepper	10	22.6972856	23.610930
	50	17.4927910	17.7098955
	100	15.8773138	15.9809598
Boat	10	23.2791065	23.9656626
	50	19.7323213	19.9094621
	100	18.2181306	18.2858974
Mandrill	10	21.4345713	21.9738948
	50	19.3367329	19.4113153
	100	18.3189125	18.3491182
Sail	10	21.7957889	22.4352654
	50	18.8889849	19.0035930
	100	17.7493283	17.7803317
Boy	10	23.7369200	24.2767233

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Image	Gaussian Noise ration	PSNR in (dB)	
		MF before WT	MF after WT
	50	20.2082717	20.4328520
	100	18.3313147	18.4174105
Arctic hare	10	27.2768261	28.1103221
	50	22.0046498	22.2923661
	100	20.0134008	20.0849186
Actor	10	23.8999225	24.6032992
	50	19.8520581	20.0262947
	100	18.1646999	18.2191217

Fig. 6 shows the Gaussian noisy Lenas's image for three levels of Gaussian noise (σ =10, σ = 50, and σ = 100) and applying median filter and threshold.

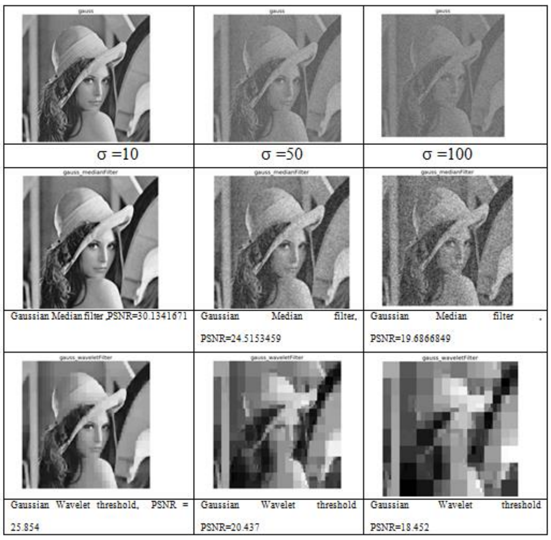

Fig. 6. Result of the PSNR value on de-nosing Lena image by only median filter and applying Wavelet threshold, noisy image corrupted by noise ratio=10,50,100

Fig. 7 shows the Gaussian noisy image for three levels of noise (σ =10, σ = 50, and σ = 100) and applying median filter before and after threshold for Lena's Image.

Fig. 7. Result of the PSNR value on de-nosing Lena image by median filter before and after threshold, noisy image corrupted by noise ratio=10,50,100

Fig. 8 shows the Gaussian noisy Cammera's image for three levels of Gaussian noise (σ =10, σ = 50, and σ = 100) and applying median filter and threshold.

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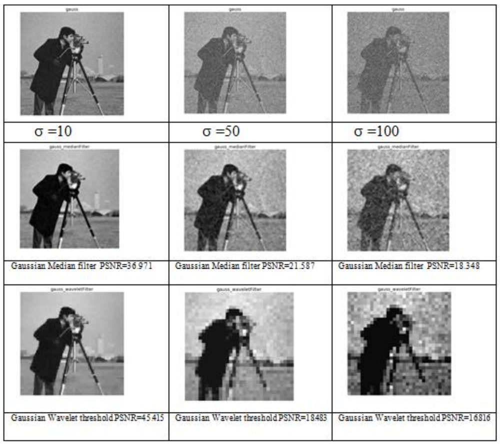

Fig. 8. Result of the PSNR value on de-nosing Camera Man image by only median filter and applying Wavelet threshold, noisy image corrupted by noise ratio=10,50,100

Fig. 9 shows the Gaussian noisy image for three levels of noise (σ =10, σ = 50, and σ = 100) and applying median filter before and after threshold for Cammera's Image.

Fig. 9. Result of the PSNR value on de-nosing Camera man image by median filter before and after threshold, noisy image corrupted by noise ratio=10,50,100

Fig. 10 shows the relation between Gaussian noise levels (σ =10, σ =50, σ =100 and PSNR. According to the results, the Camera image better than other when σ =10.

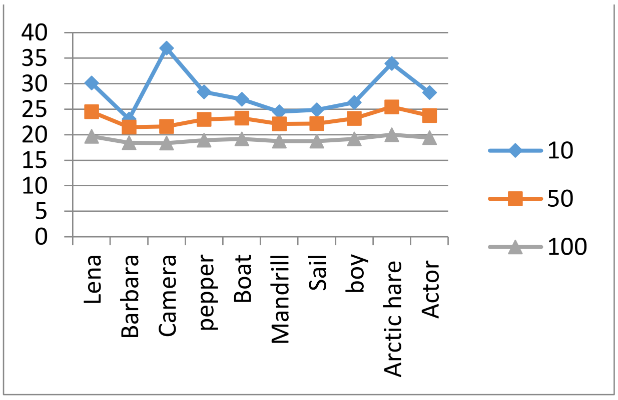

Fig. 10. PSNR values for three levels gaussain noise in Median filter

Table 5 shows the results for proposal work *Ramadhan et al* [1] for median filter without embedded system and this work, which is used embedded system such as Raspberry Pi. It clear that the values of PSNR for this work was better than the previous work. So, the Raspberry Pi is good in image denoising. The previous work has three level of noise (σ=15, σ=20, σ=25) in these values of noise the PSNR for images (Lena, Barbara and

Camera) was 26.5469, 22.3048, and 24.6562 when σ = 15 and after applying Median filter. In this work, the PSNR for images (Lena, Barbara and Camera) was 29.4795, 22.9618, and 29.6851 when σ = 15. So, this work better than previous because the PSNR higher than previous wok [1]. Also for σ=20, σ=25, this work better than previous. The Raspberry Pi has good PSNR.

Table 5. The comparison results

Images	Noise ration	MF without Raspberry Pi (2017)	MF with Raspberry Pi (this work)
Lena	15	26.5469	29.4795
	20	25.5292	28.7599
	25	24.6117	28.0639
Barbara	15	22.3048	22.9618
	20	21.9372	22.8531
	25	21.5613	22.6723
Camera	15	24.6562	29.6851
	20	24.0361	28.8509
	25	23.3887	28.06393

4. Conclusion

In this work, a new method of image de-noising is proposed. To design local median filter and wavelet threshold, the proposed method employs median filter, wavelet threshold, and median filter before and after wavelet threshold in python based on Raspberry Pi. To analysis the parameters such as MSE, PSNR to obtain High PSNR in python language is used to analysis PSNR and compare it with [1]. According to experimental results, the proposed method presents best values of PSNR for the de-noised images. The best values of PSNR for image Lena was better than camera when σ=50, and σ= 100 after applying wavelet threshold. Which PSNR of median filter = 24.5153459, and Wavelet threshold = 20.4376083. While Camera was better than Lena when σ=10, it was 36.9705523 for median filter and 45.4153470 for wavelet threshold.

To implement Raspberry Pi based on median filter and wavelet threshold, Median filter in wavelet threshold based on embedded system as a hardware and python language as a software is proposed in this work. Another work proposes a mean filter in threshold based on embedded system and python. In future work, it could propose other type of filters such as bilateral, and wiener filters in wavelet threshold. Ten images are implemented in Raspberry Pi as embedded system and python as software programming language. The processor is 2.50 GHz.

Declarations

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Conflict of interest. The author declares no conflict of interest.
Additional information. No additional information is available for this paper.

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