Comparative Analysis of Different Algorithms for Image Denoising

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***Abstract*—Image denoising attends to be the way to restore image from noise during the image was taken. There are quite a lot of algorithms on how we manage to improve broken image into better quality. In this paper we are going to compare few algorithms such as Non-Linear Means, Wavelet Transform, BM3D and Total Variation (TV) minimization algorithms. We also measure the Mean Square Error to estimate or compare original image with denoised image. Such that we can use them to improve the image quality using image denoising technique. Our experiments we use variety of noises and its level and take that image to denoise and then calculate PSNR as a result. The noises that we used are Gaussian, Speckle, Salt Pepper and Poisson.**

Keywords—Comparative, Denoising Algorithms

I. Introduction

Digital image processing is one of main part in machine learning or Computer Vision. In order to have precise result, images should be processed before analyzing into more specific research in machine learning. Images with noise is the challenges before processing with data analyzing. Without removing noise from the image, the result would be no good. Briefly noise is unwanted pixel that exists in any image taken from camera or other kind of devices. So to restore the image into a better visual quality we need denoising techniques. Difference noises, noisy level and denoising techniques will be discussed in this paper.

Generally, image noises are divided into two models. There are additive and multiplicative model.

A. Additive Model

Corrupted signal image noise can be presented by adding noise to original image. Simply defined as follow.

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

where $s(x,y)$ in the noisy image is the original bit and $n(x,y)$ is the noise which produce the corrupted signal result $w(x,y)$ locates the pixel location.

B. Multiplicative Model

Another kind of noise model is multiplicative noise. This noise present when we multiply noise signal with original signal. It is defined in the following algorithm.

$$w(x,y) = s(x,y) \times n(x,y) \tag{2}$$

Definition in the algorithm above tells us the same, but what make different is that $s(x,y)$ is multiplied by $n(x,y)$ so the noise signal will be different than additive model.

To prove that denoising algorithms are working well, we need to have make up noise using noise algorithms. These noises have their own purposes and function. There are default noises will be described as follow.

A. Gaussian Noise

Gaussian noise also known as normal noise in predefine density function. It is widely used for adding noise in image. Gaussian noise can generated randomly and separate in image and defined by the following.

$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(z-\bar{z})^2/2\sigma^2} \tag{3}$$

where z defined as intensity, $\bar{z}$ is the average (mean) value of z and σ is standard deviation. Variance of z is the standard deviation square σ^2. This function can be plot as describe in Fig.1.

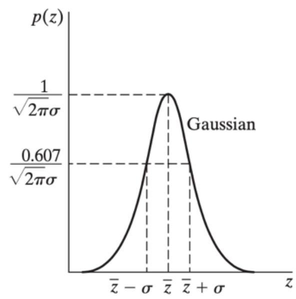

Figure 1 Gaussian Noise

B. Salt and Pepper Noise

Salt and pepper noise or impulse noise which can be either positive or negative. bipolar impulse noise also is called *salt-and-pepper* noise[1]. Impulse noise generally convert to digital as pure white and black values in an image. The values are maximum and minimum as white and black. For that reason the appearance of noise is black as 0 and white as 255 pixel.

C. Speckle Noise

Speckle noise [2][3] can be described as multiplicative noise. This noise can degrade original image into high signal noise image. This noise commonly appears in any coherent systems for instance SAR images or ultrasound images. When there is random fluctuations in signal from an object conventional radar which is not bigger than image-processing element, the speckle can appeared.

II. Denoising Algorithms

Image denoising defined as technique to restore or degrade the image, reducing the noise content of the image. In the following, we will describe some denoising algorithms basic which will be used in experimentation.

A. Spatial Domain Filtering

When there is additive noise spatial filtering can be solution to remove the noise. Spatial domain techniques are very efficient computation and require less processing resources to be implemented. This technique can be denoted by expression below.

$$g(x,y) = T[f(x,y)] \tag{4}$$

where $f(x,y)$ is the input image, $g(x,y)$ is the output image, and T is an operator on f defined over a neighborhood of point (x,y). The operator can be applied to a single image or multiple images by summing pixel by pixel of a sequence of an image noise reduction.

Basically spatial domain filtering can classified by linear and non-linear filtering techniques.

1) Linear Filters

This type of filtering will be only when there is additive noise is present[4]. The optimal filter is a mean filter for noise signal such as Gaussian noise which can be measured by mean square error. This filter will blur edges, remove lines and the other fine the detail. It specified in two sub filter such as Mean filter and Wiener filter.

a) Mean Filter

Mean filter can formed as reducing the intensity variation between one pixel to next pixel. It takes the average of pixel surrounds it. As the result it will make a pixel under mask and the image become smooth.

b) Wiener Filter

This filter remove noise from corrupted signal. Image restoration with this filter require Fourier transform of frequency-domain. To perform this filtering operation we need to know the spectral properties of original signal and the noise itself and the result will be as close as original signal. This filter can formed as the following.

$$f(x,y) = \left[\frac{H(u,v)^*}{H(u,v)^2 + \left[{Sn(u,v)}/{Sf(u,v)}\right]}\right] G(u,v) \tag{5}$$

Where $H(u,v)$ is the degradation function and $H(u,v)^*$ is its conjugate complex. $G(u,v)$ as the degraded image. $Sn(u,v)$ and $Sf(u,v)$ are the power of spectra of original image and the noise. It assumes noise and power spectra priori object.

2) Non-linear Filter

When there is a multiplicative noise, this filter can restore signal. With this filter the noise can be removed without identifying it explicitly. Median neighborhood pixel is determined by the value of output pixel. With spatial filters we use low pass filtering of group pixels and the noise covers the higher region of frequency spectrum. Basically, noise is removed and as the result image will be blurred or edge loss.

a) Median Filter

Image restoration with median filter can be done by finding median value by across window and replacing each entry in the window. Median filter frankly describe as moving window principle and use 3x3 or odd number matrices.

B. Transform Domain Filtering

Generally transform domain filtering can be divided into data adaptive and non-adaptive filters. Transform domain includes wavelet based filtering techniques and spatial frequency filtering techniques.

1) Wavelet Transform

The transform constructed by a set of building blocks which represents a signal or function[7]. The expansion of this system returns time frequency localization of signal.

C. Total Variation

This algorithm is implemented in infrared images, medical images, remote hyperspectral and multispectral images. In medical diagnosis it requires precise detection. Li and Que[6], they found that total variation (TV) filter removes noise effectively.

D. Block Matching and 3D (BM3D) Filtering

This denoising technique based on the local image sparse representation in transform domain. The sparsity is grouped 2D image patches into 3D groups. BM3D grouping and filtering is named as collaborative filtering. This denoising method can be implemented in four steps[6].

- Get image patches similar to given image patch and grouping them in 3D block
- 3D linear transform of 3D block
- Shrinkage of the transform spectrum coefficients
- Inverse 3D transformation

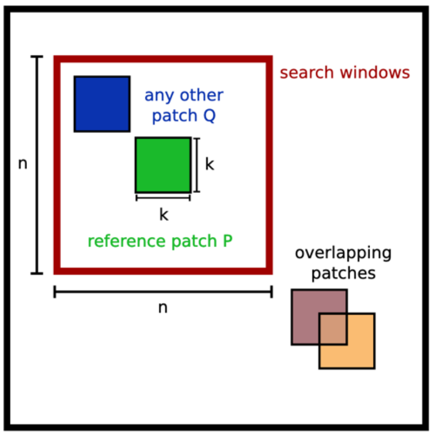

Figure 2 Patches, search windows and overlapping [6]

The process of finding similar block or finding patch can be form as follow.

$$\rho(p) = \{Q: d(P,Q) \leq \tau^{hard}\} \quad (7)$$

Where P denotes as patch whose size is $k^{hard} \times k^{hard}$ of image loop. $d(P,Q)$ is the Euclidean distance between blocks.

III. Measurements

A. Mean Square Error

Mean square error is the method where we can compare restored image to original image, calculate the different error between them. The mean square error generally defined as cumulative squared error between the restored image and original image. It is form as follow.

$$MSE = \frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N} \quad (6)$$

Where I_1 is original image and I_2 is noisy image, *m* and *n* are the height and weight of the respectively images. In our experiment the average or MSE are less than 0.1.

B. Peak Signal to Noise Ratio

Basically peak signal noise ratio defined as the expression for ratio between maximum power of signal and power of signal image noised[8]. The result or expression should be in decibel (dB) scale.

$$PSNR = 10log_{10}\left(\frac{R^2}{MSE}\right) \quad (7)$$

Where *R* is the maximal power of the signal image. The PSNR is calculated based on MSE

IV. Experimental Results

In our experiment we tried to implement various of denoising techniques. Every algorithm aims to produce better solution to remove noise from the image. Also the algorithms sometimes are not used in same fields. However we are going to implement it in script. By calculating the mean square error (MSE) and Peak Signal Noise Rate (PSNR) we try to present the best result. Moreover we also add variant of noise level and type for each experiment. We can see the result of image denoising technique as following. In Fig 3, we made experiment by taking original image (image without noise), then we add Gaussian noise (sigma) and processed it with denoising algorithms which we already described it. During denoising computation we also take MSE and PSNR to finalize the result. As a result of this denoising technique, Wavelet VisuShrink came out with blur which caused by noise elimination. On the other hand block matching 3D came out with better result and closer to original image (noise free).

Figure 3 Testing Result with Gaussian Noise

A comparative analysis has been processed between Non-linear mean, Wavelet Bayes-Shrink, Wavelet Visu-Shrink, Total Variation and Block Matching and 3D techniques. As results in table I, we found out that BM3D gave us lesser MSE with Poisson noise than Gaussian noise. On the other hand, Total Variation came out lesser using Salt and pepper noise.

TABLE I. MEAN SQUARE ERROR(MSE)

Denoising Algorithms	Noises			
	Gaussian	***Salt and Pepper***	***Speckle***	***Poisson***
Non-Linear Mean	0.02887	0.16898	0.02311	0.00172
Wavelet-Bayes Shrink	0.03414	0.13345	0.02956	0.00254
Wavelet-Visu Shrink	0.05134	0.11457	0.04504	0.00648
Total Variation	0.02854	**0.09982**	0.02811	0.02186
BM3D	**0.02446**	0.16642	**0.01976**	**0.00161**

Based on our observation during experimentation, in table II, BM3D gave best result or got highest PSNR which is 57.9996. so based on this result we conclude that BM3D can perform best. We also present the color channel of the image which is [175 201 214] and image size is 3686400 pixels, we resize to 400 by 400 and the image size become 480000 pixel.

TABLE II. PEAK SIGNAL NOISE RATIO(PSNR)

Denoising Algorithms	Noises			
	Gaussian	***Salt and Pepper***	***Speckle***	***Poisson***
Non-Linear Mean	32.9298	17.5848	34.8649	57.3961
Wavelet-Bayes Shrink	31.47461	19.63475	32.7249	54.0410
Wavelet-Visu Shrink	27.93106	20.95985	29.0679	45.9027
Total Variation	33.03135	**22.1572**	33.16168	35.3461
BM3D	**34.37153**	17.71746	**36.2236**	**57.9996**

In fig. 4 we plot sample of one our experiment using Gaussian noise, MSE value changed based on different denoising techniques. BM3D returned lowest result as 0.025. In fig.5 we calculated the

PSNR and the plotting is same sample we used in first experiment which is Gaussian noise. BM3D returned PSNR as 34.37.

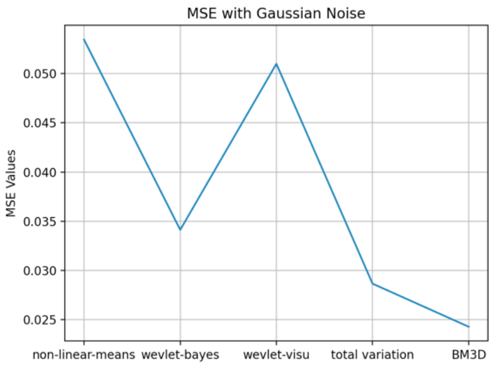

Figure 4 MSE Result

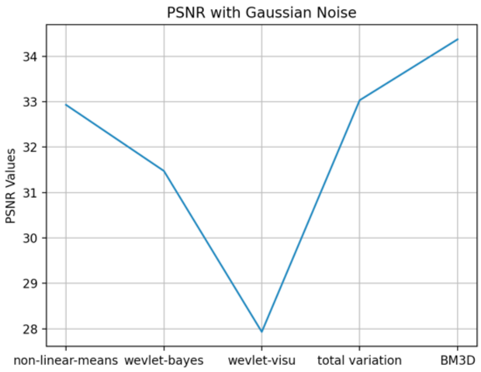

Figure 5 PSNR Result

CONCLUSION

According to out experimentation, we can conclude that returns better PSNR and has lesser MSE on BM3D than the other algorithm. Not to mention on what purpose the is analyzed for removing noises from the image. After experiment and we compare the denoising algorithms we can see that the more we high in peak signal noise ratio we performed better restoration for the noisy image and lesser peak signal noise ratio the restoration will not gave better quality. We intent to perform multiple images in future work, because with this way we can make more comparison on the denoising algorithms.

V. FUTURE WORK

As we know that computer vision has broad fields study on image processing which can be developed by using deep learning algorithms. So in this field we will try to use deep learning or artificial intelligent method to improve denoising techniques more accurately and to improve time consumed for each experiment and maybe we can manage to denoise multiple images at same time with deep learning.

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