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Comparisons Of Restored Blurred-Noisy Dental Images Using Wiener Filter And Lucy-Richardson Technique.

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***Abstract*:**

This paper attempts to compare dental images (grayscale/truecolor) degraded with blur and noise using different de-blurring filters. The image is degraded by the combination of Gaussian/Average blur and Salt & Pepper /Speckle / Poisson / Gaussian noise for different values of PSF. All the degraded images are then restored using Wiener Filter, Lucy Richardson Filter technique. Restoration by Wiener filter takes place for different values of estimated NSR and restoration by Lucy-Richardson for different iterations. The restored images are then compared on the basis of SNR, MSE and PSNR values.
This comparison are made to find which filter technique removes which combination of blur and noise on what value of PSF with high PSNR/SNR and low MSE value.

Key Terms* — *Gaussian Blur, Average Blur , PSF (Point Spread Function), , Wiener Filter, Lucy-Richardson method, estimated NSR, SNR, PSNR, MSE.

I. INTRODUCTION

Image processing means to deal with various actions to change an image. Digital image processing (DIP) is a part of signal processing where processing of digital images using various types of computer algorithm. Images are produced to record or display useful information. Due to imperfections in the imaging and capturing process, however, the recorded image , invariably represents a degraded version of the original scene. The undoing of these imperfections is crucial to many of the subsequent image processing tasks. There exists a wide range of different degradations that need to be taken into account, covering for instance noise, color imperfections (under/over-exposure, saturation), and blur.

Blurring is a form of bandwidth reduction of an ideal image owing to the imperfect image formation process[8]. It can be caused by relative motion between the camera and the original scene, or by an optical system that is out of focus. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information. The presence of noise gives an image mottled, grainy, textured or snowy appearance.

Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. The restoration of degraded image can be achieved by using de-blurring filters. Removal of blur and noise from the degraded image requires the knowledge of PSF (point spread function). When we have the knowledge of PSF, the blurred image can be restored by using Wiener filtering and Lucy-Richardson algorithm.

II. IMAGE DEGRADATION

The image degradation process can be modeled by the following equation [4]:

$$g(x,y) = H(x,y).f(x,y) + n(x,y) \quad (1)$$

where, H(x,y) degradation function or PSF (point spread function) or blur kernel, represents a convolution matrix that models the blurring that many imaging systems introduce. For example, camera defocus, motion blur, imperfections of the lenses all can be modeled by H. The values g(x,y), f(x,y), and n(x,y) represent the degraded image, the original image or input image and the additive noise respectively.

Image degradation can be performed by adding different types of blur and noise. For this paper, we have considered two types of blur, they are :

i) *Gaussian Blur* : It is the result of blurring an image by a Gaussian function. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen.

The Gaussian Blur effect is a filter that blends a specific number of pixels incrementally, following a bell-shaped curve. Apply Gaussian Blur to an image when you want more control over the Blur effect[10]. Gaussian blurring of an image depends on the length and angle of blur.

ii) *Average Blur* : The Average Blur effect smoothes the active layer or selection by softening hard edges . It produces an effect similar to that of an out of focus camera shot.

To produce this blur, filter takes the average of present pixel and the value of adjacent pixel and sets the present pixel with that of average value.

In this paper, degradation includes addition of four types of noise also. They are :

i) *Salt & Pepper Noise* : Salt and pepper noise is sometimes called impulse noise or spike noise or random noise. Salt and pepper degradation can be caused by sharp and sudden disturbance in the image signal. Generally this type of noise will only affect a small number of image pixels. When viewed, the image contains dark and white dots, hence the term salt and pepper noise[4].

ii) *Gaussian Noise* : It is also known as Amplifier noise as it is additive, Gaussian, dependent at each pixel and dependent of the signal intensity[3]. Each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value.

iii) *Speckle Noise* : Speckle noise is a random and deterministic in an image. Speckle noise can be modeled by random values multiplied by pixel values hence it is also called multiplicative noise. Speckle noise is a major problem in some radar applications[3].

iv) *Poisson Noise* : It is also known as Photon noise. Poisson noise is a basic form of uncertainty associated with the measurement of light, inherent to the quantized nature of light and the independence of photon detections.

Point Spread Function (PSF) :

The blurring is characterized by a Point-Spread Function (PSF) .It is the principle according to which one pixel becomes spread. It is also known as blurring function or impulse function.

Point Spread Function adds blur to an image which means PSF gets convolved with the image to produce a blurred image. To create PSF, two parameters are used :

i) Length of Blur
ii) Angle of Blur

This PSF is necessary at the time of blurring and de-blurring of an image.

III. IMAGE RESTORATION

Different De-blurring filters can be used to restore blurred-noisy images. Some of them are :

i) *Wiener Filter* : The Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously.

The Wiener filtering is optimal in terms of the mean square error. It minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear estimation of the original image.

ii) *Lucy-Richardson Filter* : The Richardson–Lucy algorithm, also known as Lucy–Richardson deconvolution, is an iterative procedure for recovering a latent image that has been blurred by a known point spread function. Results are different for every iteration.

PARAMETERS FOR COMPARISONS

The restored images by different filtering techniques can be compared on the basis of some parameters. Here, parameters used are- SNR(Signal-to-Noise ratio), MSE(Mean Square Error), PSNR(Peak Signal-to-Noise ratio).

The SNR is expressed in decibels :

$$SNR=10*\log10(signal/noise) \quad (2)$$

In equation(2), signal is equal to the mean of the pixel values and noise is standard deviation or error value of the pixel values.

The MSE is expressed as :

$$Error= abs\ (A-B) \quad (3)$$

$$MSE= sqrt(mean(mean(Error.^\wedge 2))) \quad (4)$$

In equation (3), Error is the difference between the absolute value of A and B,A is the filtered image and B is the original image.

The PSNR is expressed in terms of logarithmic decibel scale :

$$PSNR=20\log10(R/sqrt(MSE)) \quad (5)$$

where, R is maximum value of the pixel present in an image, MSE is mean square error between the original and de-noised image.

EXPERIMENTS AND RESULTS

All implementation work is done in MATLAB R2010a.Experiments are carried over dental images of grayscale and true-color property.

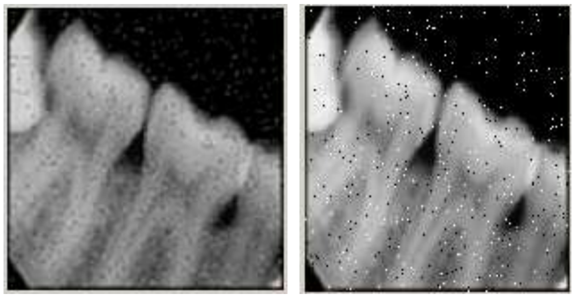
The images are degraded with Gaussian blur for different values of length(2 to 30) and angle of blur(2 to 15). Different noise are added to the image. The degraded image is restored by using Wiener filter(with different estimated NSR(between 0 to 0.1)) and Lucy-Richardson (for different iterations).The restored images are compared on the basis of SNR/MSE/PSNR values.
There are two images of grayscale and true-color.

(a) (b)

Figure 1: (a) grayscale dental image and (b) true-color dental image.

Consider figure:1(a), experiments are carried by adding gaussian blur of different blur-length and blur-angle and Salt & Pepper noise of noise-variance=0.02.It is restored by using Wiener filter(with different estimated NSR) and Lucy-Richardson (for different iterations).

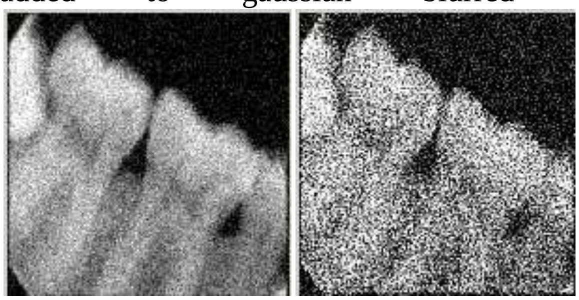
(a)



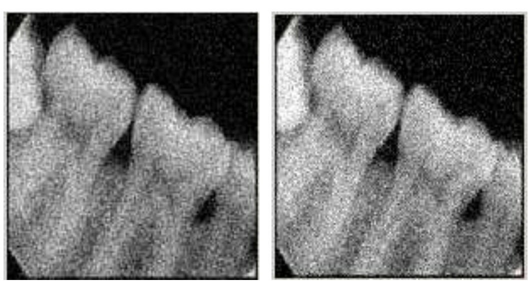
(b) (c)

Figure 2 : (a) gaussian blur of length=8 and angle=2 and salt&pepper noise is added. (b)restored with wiener filter(estimated nsr=0.01 PSNR=70.4114 dB MSE=0.0059 SNR=11.96 dB) (c) restored with LR filter (iteration=1 PSNR=69.22 dB MSE=0.0077 SNR=12.79)

Now, gaussian noise of noise-variance=0.01 is added to gaussian blurred image.



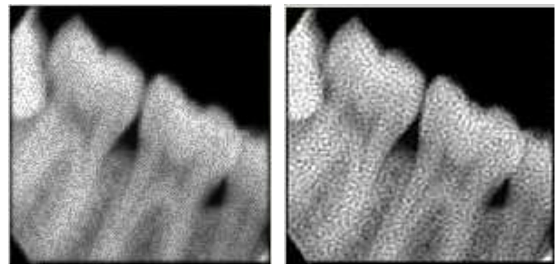
(a) (b)



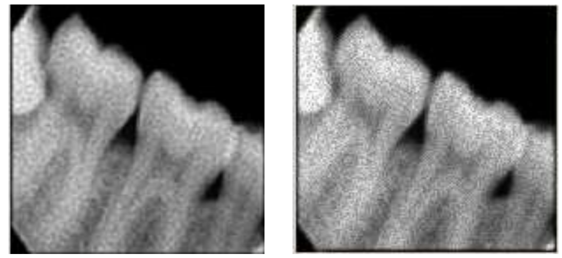
(c) (d)

Figure 3 : (a) gaussian blur of length=4 and angle=10 and gaussian noise is added. (b)restored with wiener filter(estimated nsr=0.001 PSNR=59.13 dB MSE=0.079 SNR=18.00 dB) (c) wiener filter (with estimated nsr=0.008 PSNR=68.3035 dB MSE=0.0096 SNR=13.72 dB) (d) restored with LR filter (iteration=1 PSNR=68.48 dB MSE=0.009 SNR=11.44)

Now, speckle noise of noise-variance=0.01 is added to gaussian blurred image.



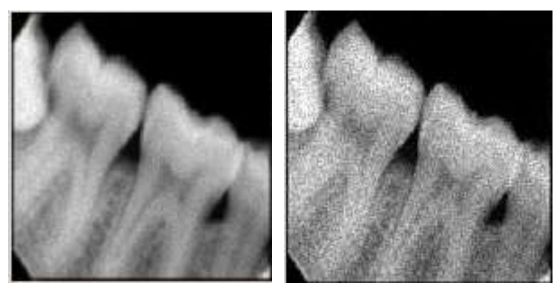
(a) (b)



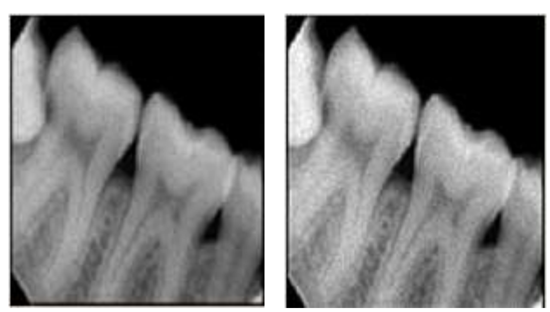
(c) (d)

Figure 4 : (a) gaussian blur of length=15 and angle=2 and speckle noise is added. (b)restored with wiener filter(estimated nsr=0.001 PSNR=71.718 dB MSE=0.0043 SNR=13.06 dB) (c) wiener filter (with estimated nsr=0.005 PSNR=74.27 dB MSE=0.0242 SNR=11.73 dB) (d) restored with LR filter (iteration=1 PSNR=72.145 dB MSE=0.0037 SNR=11.32)

Now, poisson noise is added to gaussian blurred image.



(a) (b)



(c) (d)

Figure 4 : (a) gaussian blur of length=5 and angle=3 and poisson noise is added. (b)restored with wiener filter(estimated nsr=0.001 PSNR=72.828 dB MSE=0.0033 SNR=12.78 dB) (c) wiener filter (with estimated nsr=0.01

PSNR=71.39 dB MSE=0.0042 SNR=11.19 dB) (d) restored with LR filter (iteration=4 PSNR=79.29 dB MSE=0.0007 SNR=11.37)

Consider figure:1(b), same experiments are carried over this true-color image.

Salt&Pepper noise of noise-variance =0.02 is added to gaussian blurred image.

(a)

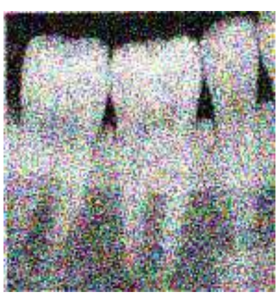
(b)

(c)

Figure 5 : (a) gaussian blur of length=10 and angle=2 and salt&pepper noise is added. (b)restored with wiener filter(estimated nsr=0.008 PSNR=67.7814 dB MSE=0.0108 SNR=13.4207 dB) (c) restored with LR filter (iteration=1 PSNR=69.21 dB MSE=0.007 SNR=14.283)

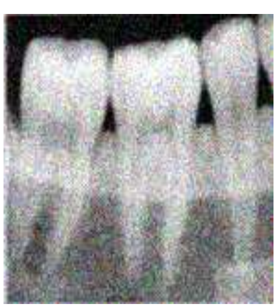
Now, gaussian noise is added of noise-variance= 0.01 to blurred image.

(a)



(b)

(c)



(d)

Figure 7 : (a) gaussian blur of length=5 and angle=10 and gaussian noise is added. (b)restored with wiener filter(estimated nsr=0.001 PSNR=60.72 dB MSE=0.055 SNR=17.98 dB) (c) wiener filter (with estimated nsr=0.005 PSNR=68.007 dB MSE=0.055 SNR=17.98 dB) (d) restored with LR filter (iteration=1 PSNR=67.981 dB MSE=0.0103 SNR=12.61)

Now, speckle noise of noise-variance=0.02 is added to gaussian blurred image.

(a)

(b)

(b)

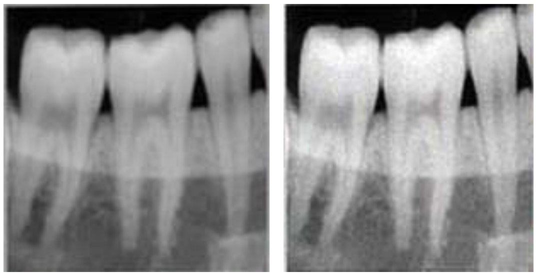
(d)

Figure 8 : (a) gaussian blur of length=15 and angle=2 and speckle noise is added. (b)restored with wiener filter(estimated nsr=0.001 PSNR=68.31 dB MSE=0.0095 SNR=14.71 dB) (c) wiener filter (with estimated nsr=0.006 PSNR=69.58 dB MSE=0.00716 SNR=13.0925 dB) (d) restored with LR filter (iteration=1 PSNR=68.405 dB MSE=0.0093 SNR=12.38)

Now,poisson noise is added to gaussian blurred image

(a)

(b)



(c) (d)

Figure 9 : (a) gaussian blur of length=5 and angle=20 and poisson noise is added. (b)restored with wiener filter(estimated nsr=0.001 PSNR=72.5899 dB MSE=0.0035 SNR=14.68 dB) (c) wiener filter (with estimated nsr=0.01 PSNR=66.428 dB MSE=0.014 SNR=13.32 dB) (d) restored with LR filter (iteration=5 PSNR=77.211 dB MSE=0.0012 SNR=13.28)

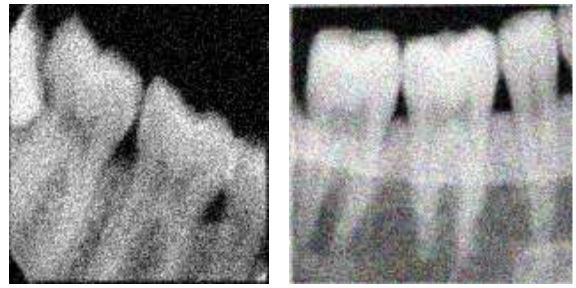
The two images are now blurred with average blur. Salt&Pepper noise of noise-variance=0.02 is added.

(a) (b)

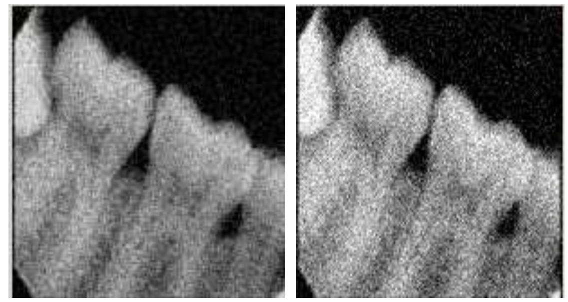
(c) (d)

Figure 10 : (a,b) average blur of length=5 and salt&pepper noise is added. (c)restored with wiener filter(estimated nsr=0.018 PSNR=66.53dB MSE=0.0144 SNR=12.574 dB) (d) restored with wiener filter (est_nsr=0.01 PSNR=66.3116 dB MSE=0.0015 SNR=15.16)

Now,gaussian noise (noise-variance=0.01) is added to average blurred images.



(a) (b

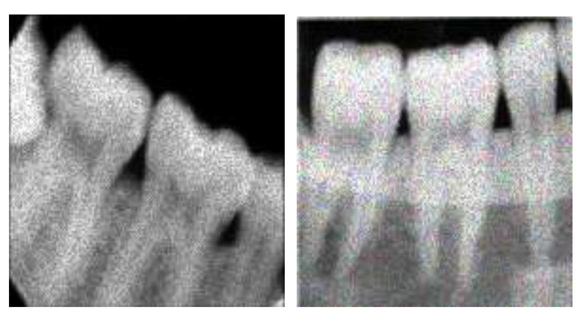


(c) (d)

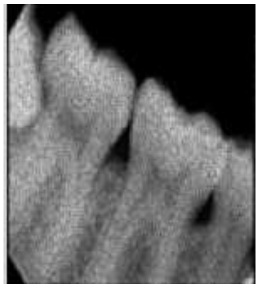
(e) (f)

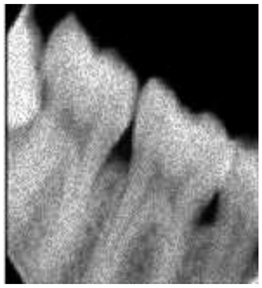
Figure 11 : (a,b) average blur of length=5 and gaussian noise is added. (c)restored with wiener filter(estimated nsr=0.01 PSNR=69.00 dB MSE=0.0081 SNR=13.079 dB) (d) retored with LR filter(iteration=1 PSNR=68 dB MSE=0.01 SNR=11.38 dB) (e) restored with wiener filter (est_nsr=0.008 PSNR=67.54 dB MSE=0.011 SNR=14.53) (f) retored with LR filter(iteration=1 PSNR=67 dB MSE=0.0103 SNR=12.67 dB)

Speckle noise(noise-variance=0.01((grayscale) and 0.02(true-color)) is added to average blurred images.



(a) (b)



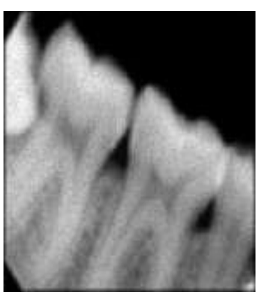


(c) (d)

(e) (f)

Figure 12 : (a,b) average blur of length=5 and speckle noise is added. (c)restored with wiener filter(estimated nsr=0.015 PSNR=68.02dB MSE=0.01 SNR=11.96 dB) (d) retored with LR filter(iteration=1 PSNR=70.41 dB MSE=0.005 SNR=11.54 dB) (e) restored with wiener filter (est_nsr=0.007 PSNR=dB MSE=0.099 SNR=14.38) (f) retored with LR filter(iteration=1 PSNR=68.71 dB MSE=0.008 SNR=12.53 dB)

Poisson noise is added to the average blurred images.



(a) (b)

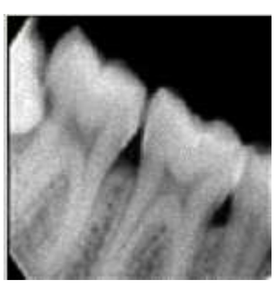


Figure 13 : (a,b) averageblur of length=6 and poisson noise is added. (c)restored with LR filter(iteration=4 PSNR=77.92 dB MSE=0.001 SNR=11.32 dB) (d) restored with LR filter (iteration=4 PSNR=76.43 dB MSE=0.001 SNR=13.258 dB)

GRAYSCALE DENTAL IMAGE			
Noises	**Gaussian Blur**		**Conclusion(Filter/PSNR/MSE/SNR)**
	Length(2 to 30)	*Angle(2 to 15)*	
Salt & Pepper	L >=5	T=2	Wiener Filter performs partially better with estimated nsr=0.01 to 0.015 67<= PSNR(approx in dB)<70 0.006<=MSE<=0.0109 11<SNR(approx in dB)<12
Gaussian	2<=L <5	T=any value	LR filter(iteration=1) performs better than Wiener filter(est_nsr=0.001 to 0.005) 68<PSNR (approx in dB)<69 0.008<MSE<0.01 11<SNR(approx in dB)<12
			Wiener Filter performs partially better with estimated nsr=0.005 to 0.01 68<= PSNR(approx in dB)<70 0.008<=MSE<0.01 13<SNR(approx in dB)<14
Speckle	L=any value	T=2	LR filter(iteration=1) performs better than Wiener filter(est_nsr=0.001) 72<=PSNR (approx in dB)<73 0.003<=MSE<=0.004 11<=SNR(approx in dB)<12
	2<=L <=5	T=any value	Wiener Filter performs partially better with estimated nsr=0.008 to 0.01 70<=PSNR(approx in dB)<72 0.004<MSE<0.005 11<SNR(approx in dB)<12
Poisson	2<L< =5	T=any value	LR filter performs better with iteration=3 to 4. 78<= PSNR(approx in dB)<80 0.0008<MSE<=0.0009 11<SNR(approx in dB)<12

Table 1: a

TRUE-COLOR DENTAL IMAGE			
Noises	**Gaussian Blur**		**Conclusion(Filter/PSNR/ MSE/SNR)**
	Length(2 to 30)	*Angle (2 to 15)*	
Salt & Pepper	L >= 5	T=2	Wiener Filter performs partially better with estimated nsr=0.008 to 0.01 66<PSNR(approx in dB)<68 0.01090<=MSE<=0.0156 13<SNR(approx in dB)<14
Gaussian	2<=L <=10	T=2	LR filter(iteration=1) performs better than Wiener filter(est_nsr=0.001) 67<PSNR (approx in dB)<68 0.01<=MSE<0.02 12<=SNR(approx in dB)<13
	2<=L <=5	T >2	Wiener Filter performs partially better with estimated nsr=0.005 to 0.01 66< PSNR(approx in dB)<68 0.010<=MSE< 0.015 13< =SNR(approx in dB)<15
Speckle	L=any value	T=2	LR filter(iteration=1) performs better than Wiener filter(est_nsr=0.001) 68<PSNR (approx in dB)<69 0.004<MSE<=0.008 12<=SNR(approx in dB)<13
	2<=L <=5	T=any value	Wiener Filter performs partially better with estimated nsr=0.005 to 0.007 66< PSNR(approx in dB)<71 0.006<MSE<=0.01 14<SNR(approx in dB)<16
Poisson	2<L<= 5	T=any value	LR filter performs better with iteration=4 to 5. 77<=PSNR(approx in dB)<78 0.001<=MSE<0.002 13<SNR(approx in dB)<14

Table 1: b

GRAYSCALE DENTAL IMAGE		
Noises	**Average Blur**	**Conclusion(Filter/PSNR/ MSE/SNR)**
	Length(2 to 30)	
Salt & Pepper	5<= L< = 6	Wiener Filter performs partially better with estimated nsr=0.01 to 0.015 67<PSNR(approx in dB)<70 0.007<=MSE<=0.01 13<SNR(approx in dB)<15
Gaussian	4< L <= 6	Wiener filter performs better than LR filter for estimated nsr=0.01 67<PSNR(approx in dB)<70 0.008<=MSE<=0.012 12<SNR(approx in dB)<14
Speckle	2 < L <= 5	Wiener Filter performs partially better with estimated nsr=0.01 to 0.015 68<PSNR(approx in dB)<71 0.005<MSE<=0.01 11<SNR(approx in dB)<13 LR filter(iteration=1) performs better than Wiener filter(est_nsr=0.001)
Poisson	2 < L <= 6	LR filter performs better with iteration=4 to 5. 77<PSNR(approx in dB)<80 0.001<=MSE<0.0007 11<SNR(approx in dB)<12

Table 1: c

TRUE-COLOR DENTAL IMAGE		
Noises	**Average Blur** *Length(2 to 30)*	**Conclusion(Filter/PSNR/ MSE/SNR)**
Salt & Pepper	5<= L< = 6	Wiener Filter performs partially better with estimated nsr=0.01 to 0.015 63<PSNR(approx in dB)<66 0.015<=MSE<=0.02 14<SNR(approx in dB)<15
Gaussian	5<= L <= 7	Wiener filter performs better than LR filter for estimated nsr=0.005 to 0.008 67<PSNR(approx in dB)<68 0.01<=MSE<=0.02 14<SNR(approx in dB)<15
Speckle	2 < L <= 6	Wiener Filter performs partially better with estimated nsr=0.005 to 0.008 66<PSNR(approx in dB)<=67 0.01<MSE<0.02 13<SNR(approx in dB)<14 LR filter(iteration=1) performs better than Wiener filter(est_nsr=0.001)
Poisson	2 < L <= 6	LR filter performs better with iteration=4 to 5. 76<PSNR(approx in dB)<78 0.001<=MSE<0.002 11<SNR(approx in dB)<13

Table 1: d

Table.1 (a), (b), (c), (d) shows the summary of comparisons of restored blurred dental images with different noises by two different filters

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