Critical Performance Analysis and Comparison of Restoration for Diversified Field Images using Least Square Regression (LSR) Technique

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Abstract

In this Paper, we describe Least Square Regression Technique to design three algorithms. Automatic estimation of parameters and selection of restoration methods for diversified field images is done in proposed model. Image restoration plays an important role in computer vision and image analysis in special and transform domain. For comparative study, experimental results on test images demonstrate that the proposed technique performs better than the slandered algorithms on the basis of PSNR.

1. Introduction

Images are produced to record or display useful information in picture format. Due to imperfections in the process of capturing, the recorded image represents a degraded version of the original scene. Removing these imperfections is very difficult task form images many times. There exists a wide range of different degradations, which are to be taken into account, for instance noise, geometrical degradations, illumination, colour imperfections and blur. The main purpose of restoration is to obtain high quality of image from the low or degraded quality of image. In the use of image restoration methods, the characteristics of the degrading system and the noise are assumed to be known a priori [4]. The synthetic noises i.e. Salt and P-epper, Gaussian, Speckle, and Poisson are used. In practical situations, however one may not be able to obtain this information directly from the image formation process.

The method of least square is to determine the best fit line to data. For this, it uses some calculus and algebra. To find out the best approximation to the data, first task is to calculate the not only the solution for the least squares as the mean of some values having less variation or values having more variation will be same. Hence standard deviation is the solution to this to find out the errors easily. If the difference between mean and individual pixel value is more, ultimately the error will large and vice versa.

There exist so many types of images having their own characteristics. For example, images are taken from long distance. It contains the effect of electromagnetic radiation, variation of density of light. Natural Image: various natural sceneries, flower, plants, animals etc. are included in the natural images. Arial Image: Satellite images and Telescopic images are the part of Arial image. Medical Image: It includes X-rays, CT scan, and MRI's. It has the characteristics of human body or internal parts of a body [7]. Underwater image: it includes the images which are taken under the water which differ the refractive indices under water and on air.

On account of all these, application is designed which takes input as image and noise, it observes and analyses the type of image and the type of noise and recommends the most suitable restoration technique. To restore the images, so many techniques are available. Considering some filters, designing is done to restore or to de-convolve the degraded images. Least square regression technique is used to design the filters.

2. Background review

In general model of image restoration, the degraded image is restored automatically. First the image is browsed, and all blur and noises are occur in spatial domain; they are Gaussian, Poisson, Speckle, and Salt and Pepper noise. According to model, Gaussian noise is distributed over signal while transmission which has bell shaped PDF. Salt & Pepper is an impulse noise; it is generally caused by malfunctioning in picture element by manufacturing defects [9]. Speckle noise occurs in almost all coherent imaging system such as aperture radar imagery etc. The Poisson distribution is a discrete distribution that takes non-negative integer value. After the addition of noise, the resultant image will be degraded version of the original one. This noisy degraded image when applied to any restoration filter, noise in that image may be removed partially. Image browsed in the model can be colored or grayscale. Then it is scaled to 256×256 and then applied to the working model. Each pixel in 256×256 image has two values of each dimension. For this model, three filters i.e. Wiener Filter, Regularized Filter and Blind Deconvolution have designed. The quality of the results was evaluated both visually and in terms of PSNR, Mean Square Error (MSE). Detailed comparisons of filtering with different distortion metrics like ISNR, SC, NAE, AD, MD and NCC were evaluated, and analyzed that the proposed model yields significantly. Designed model for the restoration purpose is mentioned below:

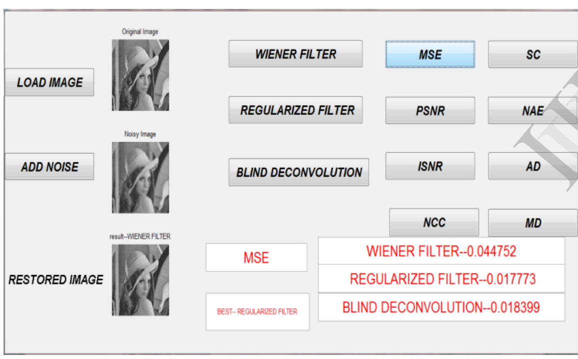

Figure 1. Model in MATLAB

Parameter values are shown in this above model. Also by calculating maximum or minimum value, this shows the suitable filter for the combination of image as well as noise. Here blur as well as Gaussian Noise has added.

3. Restoration Techniques

3.1. Wiener Filter Technique

Let the function of original image is f_k. Here is some response function of the system h_k. Synthetic noise has added to the system of each image. Let the added noise be n_k. As the result of the processing of true image, degraded image is formed. That degraded version of image is g_k [14].

$$g_k = f_k \otimes h_k + n_k \quad (1)$$

Where as usual we write $\otimes$ for convolution and display the result in both the time domain and the frequency domain. Also, assume the sampling interval δ is one; otherwise sums in the time domain below need to be multiplied by δ and sums in the frequency domain need to be divided by δ. Therefore in frequency domain convolution is transformed to multiplication.

$$G_j = F_j.H_j + N_j \quad (2)$$

In the absence of noise, if we know the response functions of the apparatus we already know how to find the true image.

$$F_j = \frac{F_j.H_j}{H_j} \quad (3)$$

Now we want to find the optimal Wiener filter, w_k or W_j which, when applied to the measured signal and de-convolved by the instrument response, gives us an estimate of the true image:

$$F_j^{'} = \frac{G_j.W_j}{H_j} \quad (4)$$

Note that it gives us the smeared signal from the system from the measured signal.

Now we have estimated function of image $F_j^{'}$ and original image function F_j. Sum of square of the difference is $\sum_{k=0}^{n-1}(F_j - F_j^{'})^2$. To get the minimum error Sum of square of the difference should ideally be zero and minimum as possible. Hence $E = \sum_{k=0}^{n-1}(F_j - F_j^{'})^2$ is minimized. We have to minimize

$$E = \sum_{k=0}^{n-1}\left(\frac{F_j.H_j}{H_j} - \frac{G_j.W_j}{H_j}\right)^2 \quad (5)$$

Hence we have tried to minimize this equation for the implementation of wiener filter using least square regression technique.

3.2. Regularized restoration Technique

Regularized restoration provides results similar to Wiener filter but is justified by a very different viewpoint. Less prior information is required to apply regularized restoration. We have established a technique for kernel based, regularized least squares regression methods, which uses the non-zero value for given conditions of the associated integral operator as a complexity measure [15]. We then use this technique to derive learning rates for these methods. Here, it turns out that these rates are independent of the exponent of the regularization term.

Given a training set $((x_1, y_1)....(x_n, y_n))$ sampled from some unknown Point Spread Function (PSF) 'P' on N*N matrix, the goal of least squares regression is to find a function R.

$$R_{E,P}(f) = \int E(y, f(x))dp(x, y) \qquad (6)$$

Where E is the least squares error, i.e. $E(y,t) = (y-t)^2$, is close to the optimal risk. Means when the value of error E is minimum the risk is minimum, when the value of risk increases the risk is also increases. Therefore at the value of infinity, risk R shows maximum value.

$$R_{E,P}(f) - R'_{E,P}(f) = \int | f - f' |^2 dp_x \qquad (7)$$

p_x - denotes the marginal distribution of p which is minimizer of $R_{E,P}(f)$. f' is well known regression function. We design the least square technique with kernel based method. Hence observed verifiable risk is

$$R_{E,V}\, f(x) = \frac{1}{n}\sum_{i=1}^{n}(E(y_i, f(x_i)) \qquad (8)$$

3.3. Blind Deconvolution

In many areas, the problem of distortion of image by unwanted point spread function (PSF) is occurred. In case of known PSF, the recovery of distorted image is relatively easy and straightforward. When original true image and PSF are unknown, Blind deconvolution is a significantly more demanding problem and occurs [13]. The basic model considered as

$$g(x, y) = f(x, y) \otimes h(x, y) + n(x, y) \qquad (9)$$

where f(x,y) represents the true original image, h(x,y) is PSF, and g(x,y) the observed image. The term n(x, y) models the inevitable noise in the imaging process as an additive component. Symbol $\otimes$ represents two-dimensional convolution. Alternatively the convolution can be represented in the Fourier domain as

$$G(u,v) = F(u,v)H(u,v) + N(u,v) \qquad (10)$$

Here capital letters are used to indicate the Fourier transform of images. The information available in blind de-convolution is g(x,y) i.e. observed image and it is usually required to recover the original image f(x, y). The additional assumptions should be taken in the form of some a priori knowledge of either the object or the PSF to avoid an infinite number of possible solutions. In incoherent imaging, these assumptions usually take the form of a positive constraint on either the image or the PSF. Another constraint that is often employed is a support constraint, which depends on a blurred image being larger than either the true image or the psf. In practice a support constraint is implemented by restricting the extent of the recovered image and PSF to regions smaller than the extent of the blurred image. A final constraint which we employ in this technique is to assume that the spectrum of the unknown PSF is a lowpass filter, whereupon the convolution can be assumed to be a low resolution image of the true object. This is a powerful constraint since f(x, y) (function of true image) is common to all the blurred images [18].

By minimizing the error matric, image is restored by blind de-convolution using the least squares as follows:

$$E_C = \sum_{x,y} | g(x, y) - f(x, y) \otimes h(x, y) |^2 \qquad (11)$$

It indicates the deviation from being a perfect match to the observed convolution. We refer to E_C as the convolutional error.

4. Experimental Results

For the analysis of system, three images of each category Arial images, Medical images, Natural images, and Underwater images have taken.

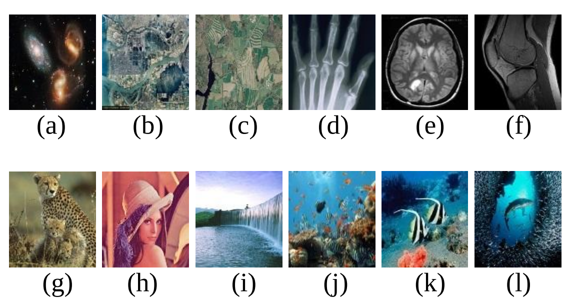

Figure 2. Database of Images for Experimental Results (a) Telescopic, (b) Satellite, (c) Airplane, (d) X-ray, (e) MRI, (f) CT-Scan, (g) Animal, (h) Lena, (i) Waterfall, (j) Fish 1, (k) Fish 2, (l) Fish 3

ISSN: 2278-0181
Vol. 2 Issue 10, October - 2013

TABLE I
PSNR VALUES OF FILTERS FROM DIVERSIFIED FIELD IMAGES

Wiener Filter with Least Square Regression												
	Arial Images			Medical Images			Natural Images			Underwater Images		
	telescopi	satellite	airplan	X-ray	MRI	CT-	Animal	Lena	Waterfal	fish 1	fish2	fish3
Gaussia	60.5284	58.375	59.245	59.258	59.094	60.989	59.899	60.055	59.2898	59.573	59.512	58.764
Poisson	63.329	58.127	60.426	65.058	60.791	63.201	59.576	61.622	62.2647	60.332	61.011	59.088
Speckle	59.864	56.074	57.529	59.807	58.302	59.273	56.058	56.944	57.2241	57.263	57.824	57.458
Salt &	64.5425	59.528	62.146	66.939	57.980	64.179	60.842	62.607	63.9179	61.619	62.54	60.954

Wiener Filter without Least Square Regression												
	Arial Images			Medical Images			Natural Images			Underwater Images		
	telescopi	satellite	airplan	X-ray	MRI	CT-	Animal	Lena	Waterfal	fish 1	fish2	fish3
Gaussia	60.5419	58.385	59.224	59.245	59.103	60.977	59.905	60.062	59.2781	59.571	59.551	58.764
Poisson	63.329	58.127	60.426	65.058	60.791	63.201	59.576	61.622	62.2647	60.332	61.011	59.088
Speckle	59.8592	56.074	57.531	59.776	58.306	59.269	56.058	56.960	57.2158	57.260	57.822	57.461
Salt &	64.5425	59.528	57.531	66.939	63.023	64.179	60.842	62.607	63.9179	61.619	62.54	60.954

Regularized Filter with Least Square Regression												
	Arial Images			Medical Images			Natural Images			Underwater Images		
	telescopi	satellite	airplan	X-ray	MRI	CT-	Animal	Lena	Waterfal	fish 1	fish2	fish3
Gaussia	56.0939	55.849	55.982	56.103	56.193	56.401	56.027	56.079	56.2186	56.017	56.038	55.925
Poisson	66.6428	60.938	63.530	70.712	65.851	68.161	63.861	65.633	66.4335	64.069	61.011	62.271
Speckle	52.6127	49.500	49.461	50.054	50.887	52.260	49.606	48.960	48.2038	49.702	50.044	51.157
Salt &	69.7565	63.869	66.506	71.909	56.094	70.332	66.696	68.608	69.0814	67.076	67.921	65.581

Regularized Filter without Least Square Regression												
	Arial Images			Medical Images			Natural Images			Underwater Images		
	telescopi	satellite	airplan	X-ray	MRI	CT-	Animal	Lena	Waterfal	fish 1	fish2	fish3
Gaussia	60.5419	58.385	59.224	59.245	59.103	60.977	56.027	56.030	56.153	56.017	56.067	55.984
Poisson	63.329	58.127	60.426	65.058	60.791	63.201	63.861	65.633	66.4335	64.069	64.913	62.271
Speckle	59.8592	56.074	57.531	59.776	58.306	59.269	49.589	48.977	66.4335	49.637	50.007	51.121
Salt &	64.5425	59.528	57.531	66.939	63.023	64.179	66.696	68.608	69.0814	67.076	67.921	65.581

Blind Deconvolution with Least Square Regression												
	Arial Images			Medical Images			Natural Images			Underwater Images		
	telescopi	satellite	airplan	X-ray	MRI	CT-	Animal	Lena	Waterfal	fish 1	fish2	fish3
Gaussia	56.4264	56.139	56.307	56.440	56.524	56.736	56.350	56.409	56.5501	56.342	56.367	56.228
Poisson	66.5059	60.812	63.397	70.586	65.665	67.997	63.719	65.482	66.2756	63.919	64.763	62.13
Speckle	52.946	49.829	49.792	50.388	51.219	52.598	49.939	49.294	48.5358	50.033	50.372	51.488
Salt &	69.556	63.673	66.313	71.915	56.421	70.212	66.496	68.402	68.8785	66.866	67.714	65.383

Blind Deconvolution without Least Square Regression												
	Arial Images			Medical Images			Natural Images			Underwater Images		
	telescopi	satellite	airplan	X-ray	MRI	CT-	Animal	Lena	Waterfal	fish 1	fish2	fish3
Gaussia	61.4721	58.434	60.229	62.320	61.209	61.624	60.068	61.186	61.4234	60.404	60.896	59.350
Poisson	65.3619	58.780	61.065	67.400	63.54	64.728	60.758	62.620	63.0801	61.340	62.039	59.283
Speckle	58.1923	54.832	55.000	55.656	56.980	54.144	55.064	54.462	53.6554	55.200	55.725	52.953
Salt &	68.1844	60.826	55.000	69.052	66.503	60.820	62.625	64.403	64.9852	63.360	64.140	62.647

Noises of Gaussian, Poisson, Speckle, Salt and pepper noise have added to all the images. These all results are taken on the basis of PSNR. For example, for Lena image, Gaussian noise is applied and PSNR=60.05dB is obtained as a result. The filter having large value of PSNR, considered as best filter for that combination of image and noise.

The figures shown in figure 3 in which the output of three images of each category are seperatly taken. On the basis of PSNR, the images have analysed. Here in all the gragh categorywise name of images in fig. 3 are mentioned on X –axis and PSNR in db have shown on Y- axis. Also on each image, four noises have mentioned. As Peak Signal to Noise Ratio, takes the ratio of Peak Signal power to the power of coruppted noise. It can be easily find with the help of MSE value. MSE measures the average of the squares of the error. PSNR in decible is

$$PSNR = 20\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \tag{13}$$

Here MSE can be calculated as

$$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{K=1}^{N}(x_{j,k} - x'_{j,k})^2 \tag{14}$$

It is most easily defined via the mean squared error (MSE) which for two M×N monochrome images i and k where one of the images is considered a noisy approximation of the other.

The Performance Analysis of individual filters with and without LSR is as follows:

4.1. Wiener Filter

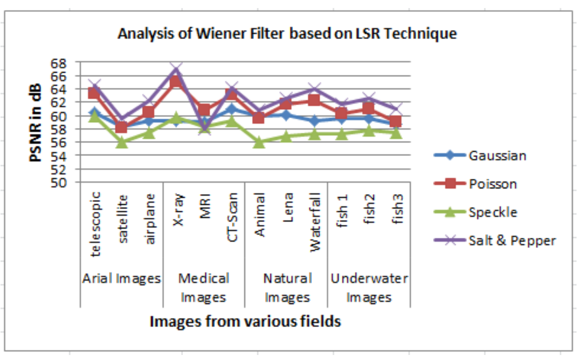

Figure 3. Performance of Wiener Filter with Least Square

Figure 3 shows the effect of Wiener filter on the various fields of images. For X-ray images the result of Wiener comparatively gives good results. Broadly the Wiener filter gives better PSNR for Medical images. In almost all restored images the value of PSNR is large when Salt and Pepper noise is applied. Variation in results is high and gives wide range of PSNR value.

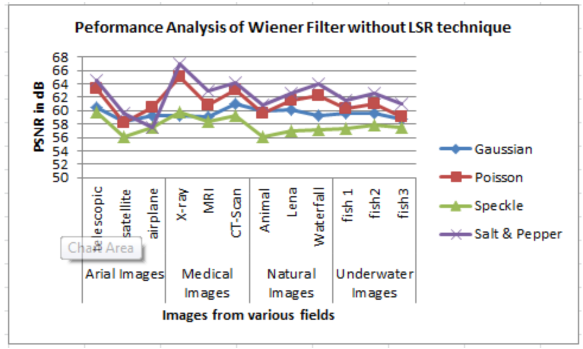

Figure 4. Performance of Wiener filter without least square

Performance of Wiener Filter with Least Square and Without Least Square is almost same. i.e. the PSNR values of techniques are near about same.

4.2. Regularized Filter

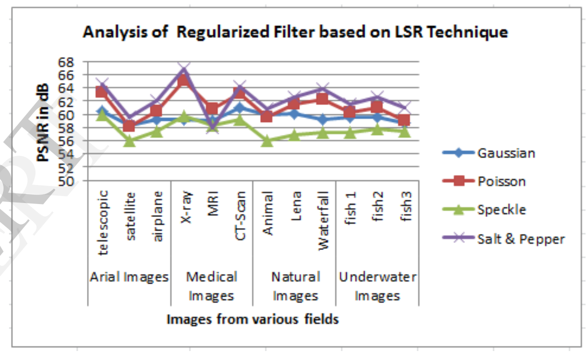

Figure 5. Performance of Regularized Filter with Least Square

Regularized filter have greater PSNR for Salt and Pepper noise, also for Poisson noise. This filter gives average but better PSNR in the range 50 to 70 for all types of images and noises. This filter gives good results for Medical and Natural images.

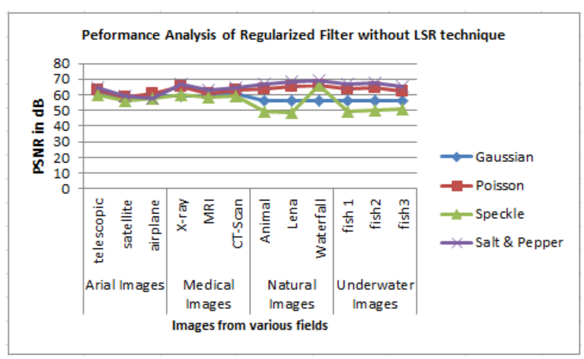

Figure 6. Performance of Regularized filter without Least square

For Arial Images and Medical Images The performance of Regularized Filter with Least Square is more than Without Least Square.

4.3. Blind Deconvolution

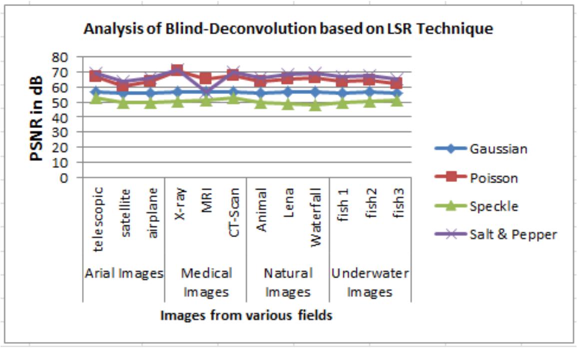

Figure 7. Performance of Blind Deconvolution with least square

Blind deconvolution has better performance for Gaussian noise compared with the other filter, average PSNR= 56dB. It gives average results for all type of images.

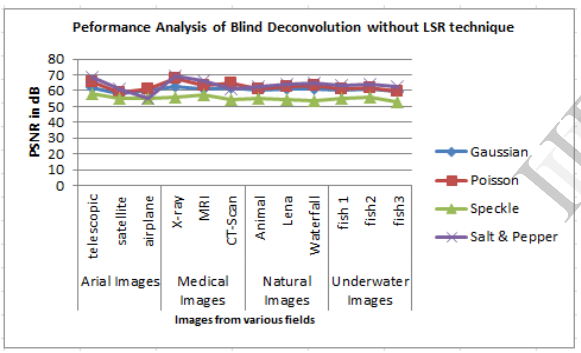

Figure 8. Performance of Blind Deconvolution without least square

Performance is better for the combination of Arial Images with salt and pepper noise as well as the combination of Arial Images with Poisson Noise. Also overall performance of Blind Deconvolution is better in case of Salt & Pepper Noise, Poisson Noise and Gaussian Noise is more as compared to without least square technique.

5. Conclusion

We have implemented three restoration techniques based on LSR to restore the diversified images (Medical, Arial, Natural, and Underwater). Performance of the Wiener filter, Regularized restoration and Blind deconvolution compared to each other using PSNR values. Proposed technique will compare automatically to give suitable compilation of images and specific type of synthetic noise for optimum selection. LSR based restoration techniques are compared some state of art restoration techniques which are implemented only for single type of image and noise. After analysis of three techniques it is found better than some existing restoration methods.

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