Scientific Journal of Impact Factor (SJIF): 4.72
e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406
International Journal of Advance Engineering and Research Development
Volume 4, Issue 7, July -2017

Performance Analysis of Adaptive Filters for Image Restoration

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Abstract- *Generally, images in course of capturing and transmitting are frequently degraded due to channel effects or uncertain conditions. These effects introduce different noises such as Gaussian Noise, Impulse noise (Salt & Pepper Noise) and speckle Noise. Therefore, retrieved images are highly noise corrupted because the image contents are more attenuated or amplified. The implementation of adaptive algorithms for restoration is being carried out by estimating noise and removing the noise through system identification and signal enhancement with Wiener, RLS & EKF algorithms. Our goal was to find a suitable adaptive algorithm for noise removal in gray scale image &restore the original image from the degraded image. Also comparing Wiener, RLS, and EKF based on their performance metrics. The performance is evaluated by means of Human Visual System, quantitative measures in terms of MSE, PSNR, SSIM, FSIM, VIF, & IQI and by graphical measures. The image restoration and further processing algorithms are simulated in MATLAB environment.*

Keywords—*Impulse Noise; Recursive Least Square (RLS); Extended Kalman Filter (EKF);*

I. INTRODUCTION

Image restoration and filtering is the significant field of digital image processing, which is used to restore the degraded or distorted image contents & denoising. The goal of de-noising is to remove noise by preserving important image details and to acquire good quality image. The optimal choice of filter is important and shows a vital role for images de-noising. Where Satellite images are captured and transmitted in wireless channel they are usually degraded due to noisy channel effects [1]. Mostly the image degradation is caused by channel noise and random atmospheric turbulence [2, 3]. As a result, the channel contents are either attenuated or amplified during transmission in wireless channel different noises, i.e. Gaussian Noise, Impulse Noise and speckle Noises should exist and distorted the satellite images. During few decades of progression, the researchers have developed and implemented different well-organized techniques for image restoration and de-noising. Wiener filter is one of the classical approach to the image restoration. The wiener filter is no longer optimal for image restoration because of the lack of prior information or estimation about original image, it may results undesirable restoration. When the estimation of degraded function and covariance measurement of original image is difficult, the use of adaptive filters can offer performance improvement over the wiener filter.

The adaptive filtering is one of most suitable technique especially for noise cancellation in signal and image processing applications [4]. The adaptive filters are self-adjusted and have an ability to track variations in the signal or parameters of time-varying system to meet the performance factors. The performance is upgraded automatically by adjusting the filter coefficients and impulse response of respective input through algorithm [6, 7]. The adaptive filter efforts to model output signal for correlation with its input signal iteratively [5, 6]. Thus it is extensively used in denoising signals. The efficiency of adaptive filter mainly depends on design techniques of filter and adaptation algorithm. Adaptive algorithms broadly classified as Stochastic Gradient Approach and Least Squares Estimation (LSE).One of the approach to the development of least square estimation (LSE) is recursive least square (RLS) algorithm. The recursive least square algorithm is more popular because it has a fast convergence rate and it requires less data storage. RLS can be seen as a special case of the well-known kalman filter, which itself is a form of LSE. RLS is basically the update step of the kalman filter i.e., the estimated state is updated using only the available measurement. Whereas the kalman filter also has a prediction step but a model of the system is used to predict the evolution of the states even in the absence of measurement. The general configuration of an adaptive FIR filter is shown in *Figure.1*.

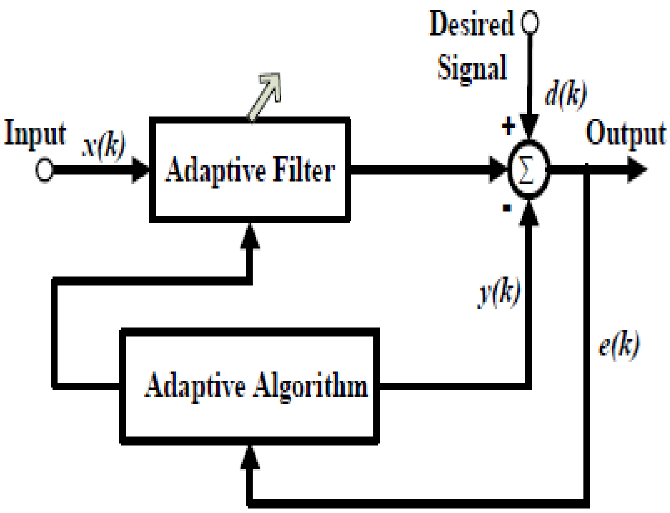


Figure.1: General Configuration of an Adaptive Filter.

In this paper, we have presented a RLS, EKF for optimum restoration of images. The main objective of this project is to restore the gray scale images which are affected by the Gaussian, speckle, and salt and pepper noises using adaptive algorithms (RLS and EKF) & also comparing the results wiener filter results. The image restoration and further processing algorithms are simulated in MATLAB environment. Finally, the performance is examined by means of Human Visual System (HVS), quantitative and graphical measures. Our goal is to achieve improved value of Peak Signal to Noise Ratio (PSNR).

II. METHODOLGY FOR IMAGE RESTORATION

Image Restoration is to recover an original image from affected image by different types of Noises like Gaussian Noise, Speckle Noise and impulse Noise. First step in image restoration process, degradation function is measured based on algorithm then after image is restored and enhanced. The system architecture for image restoration is shown in *Figure. 2*. Which effectively describes the image restoration and enhancement scheme.

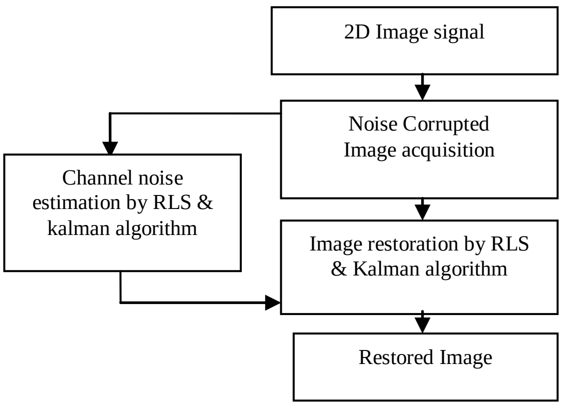


Figure.2: System architecture for image restoration

A. wiener Filter

Wiener filter is one of the earliest and best known approach to linear image restoration. A significant amount of prior knowledge is required for the wiener restoration, including knowledge about degradation function, the covariance of the original image and of the noise signal. The wiener filter is optimal in terms of mean square error when the original image and noise are statistically independent and zero mean.

Wiener filter formulation:

A wiener filter seeks an estimate f that minimize the statistical error function.

$$e^2 = E\left\{\left(f - \hat{f}\right)^2\right\} \qquad (1)$$

Where E {.} is the expected value of argument. The minimum of error function in eq. (1) is given in the frequency domain by the expression.

$$\hat{F}(u,v) = \left[\frac{1}{H(u,v)} \frac{|H(u,v)|^2}{|H(u,v)|^2 + \frac{S_\eta(u,v)}{S_f(u,v)}}\right] G(u,v) \qquad (2)$$

Where, H $(u$, v) = the degradation function

$|H(u,v)|^2 = H^*(u,v)H(u,v)$

$H^*(u,v)$ = the complex conjugate of H $(u$, v)

$S_\eta(u,v) = |N(u,v)|^2$ the power spectrum of the Noise

$S_f(u,v) = |F(u,v)|^2$ the power spectrum of the undegraded image.

$G(u,v)$ is the transform of the degraded image

If the noise $S_\eta(u,v)/S_f(u,v)$ is zero then the noise power spectrum vanishes and the Wiener filter reduces to the inverse filter. If the noise $S_\eta(u,v)/S_f(u,v)$ is large.

B. Recursive Least Square (RLS) Adaptive Filter

The RLS algorithm is recognized as to follow fast convergence rate, when the range of Eigen value is large for the correlation matrix of input signal. This algorithm gives outstanding performance when operational in time variable conditions [6, 8]. The objective of this algorithm is to select the filter coefficients in such a way that the output signal *y(k)* will match accurately with desired signal d(k) in least squareestimate [9]. These advantages are achieved at the cost ofincreased computational limitations and other instabilityfactors [4, 6]. The RLS algorithm is implemented bycomputing known initial conditions and then updating theprevious estimate based on information kept in the recent datasamples [6]. Which is done by estimating the least square offilter coefficients *w(n-1)* at iteration *n-1*, by calculating theestimate of coefficients at iteration *n* by means of recentlyavailable information [4]. The Eq.3 describes the input vector x(k) with N filter order.

$$x(k) = [x(k)\ x(k-1) \dots\dots\dots x(k-n)]^T \qquad (3)$$

The objective function for LS algorithms is specified by

$$\xi^d(k) = \sum_{i=0}^{k} \lambda^{k-i} \varepsilon^2(i)$$

$$\xi^d(k) = \sum_{i=0}^{k} \lambda^{k-i} \varepsilon^2(i)[d(i) - x^T(i)w(k)]^2$$

Where

$w(k) = [w_0(k) w_1(k) \dots\dots\dots w_N(k)]^T$is the filter coefficients, ε(i)=a-posteriori output error and λ=forgetting factor, ranges from 0<λ≤1. the expression for filter coefficients w(k) is given in eq.4

$$w(k) = R_D^{-1}(k)P_D(k) \qquad (4)$$

Where$R_D^{-1}(k)$ represents the inverse correlation matrix the input signal and $P_D(k)$ defines the deterministic cross correlation matrix among the input and desired signal

Computational Initialization of RLS Algorithm

$$s_D(-1) = \delta I$$

Where, δ should be the inverse estimate of input signal.

$$P_D(-1) = x(-1) = [0\ 0 \dots 0]^T$$

$$D_0 fork \geq 0$$

$$S_D(k) = \frac{1}{\lambda}\left[S_D(k-1) - \frac{S_D(k-1)x(k)x^T(k)S_D(k-1)}{\lambda + x^T(k)S_D(k-1)x(k)}\right]$$

$$P_D(k) = \lambda P_D(k-1) + d(k)x(k)$$

$$w(k) = S_D(k)P_D(k)$$

if required then evaluate

$$y(k) = w^T(k)x(k)$$

$$\varepsilon(k) = d(k) - y(k$$

C. Extended kalman filter:

The EKF is the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance. Using Dual extended kalman filter degradation function is estimated by adjusting the weights based on the time & measurement updated equations. However the higher orders EKFs tend to only provide performance benefits when the measurement noise is less.

The most important part of applying EKF is model creation using knowledge of mathematics to create transition function which is non-linear for unknown parameter in each state of estimation. There are 2 models for EKF including

State Model: $x_{k+1} = f(x_k; u_k + w_k)$ (5)

Where x is the state model which composes of parameters using for prediction in each state x_{k+1} is the next state that we should get the predicted data from using transition function which is non-linear function
$u_k$is the control data which is optional w_k is Gaussian white noise

Measurement Model: $z_k = h(x_k + v_k)$ (6)

Where
z_k is the measurement model
$v_k$is Gaussian white noise

For a *linear* model with *known* parameters, the Kalman filter (KF) algorithm can be readily used to estimate the states [10]. At each time step, the filter computes the linear least squares estimate $\hat{x}(k)$ and prediction $\hat{x}^{-}(k)$ as well as their error covariance's, $p(k)$ and $p^{-}(k)$. In the linear case with Gaussian statistics, the estimates are the minimum mean square estimates. With no prior information on x, they reduce to the maximum likelihood estimates. When the model is nonlinear, the KF cannot be applied directly, but requires a linearization of the nonlinear model at the each time step. The resulting
algorithm is called the extended Kalman filter (EKF), and effectively approximates the nonlinear function with a time-varying linear one. The EKF algorithm is as follows:

Time update for state estimation

- project the state ahead

$$\hat{x}^{-}(k) = F[(\hat{x}(k-1), \hat{w}(k-1)$$

- project the error covariance ahead

$$P\bar{\hat{x}}(k) = AP\hat{x}(k-1)A^T + B\sigma_v^2 B^T,$$

$$Where\ A = \frac{\partial F[\hat{x}, \hat{w}]}{\partial \hat{x}}\bigg|\hat{x}(k-1)$$

Measurement update for state estimation

- Compute the kalman gain

$$K(k) = P\bar{\hat{x}}(k)C^T(CP\bar{\hat{x}}(k)C^T + \sigma_n^2)^{-1}$$

- update estimate with measurement z_k

$$\hat{x}(k) = \hat{x}^{-}(k) + K(k)(y(k) - C\hat{x}(k))$$

- update the error covariance

$$P\hat{x}(k) = (I - K(k)C)P\bar{\hat{x}}(k)$$

Because, the model for the image is not known, the standard EKF algorithm cannot be applied directly. We approach this problem by constructing a separate state-space formulation for the underlying weights as follows:

$$w(k) = w(k-1)$$
$$y(k) = f\big(x(k-1)w(k)\big) + v(k) + n(k)$$

These state space equations for the weights allow us to estimate them with a second EKF.

Time update for weight estimation

- project the weight ahead

$$\hat{w}^{-}(k) = \hat{w}(k-1)$$

- project the error covariance ahead

$$P\bar{\hat{w}}(k) = P\hat{w}(k-1)$$

Measurement update for weight estimation

- compute the kalman gain

$$K\hat{w}(k) = P\bar{\hat{w}}(k)H(k)^T(H(k)P\bar{\hat{w}}(k)H(k)^T + \sigma_n^2 + \sigma_v^2)^{-1}$$

- update estimate with measurement z_k

$$\hat{w}(k) = \hat{w}(k) + K\hat{w}(k)(y(k) - CF(\hat{x}(k-1), \hat{w}(k-1)))$$

$$Where\ H(k) = \frac{C\partial F[\hat{x}, \hat{w}]}{\partial \hat{w}}\bigg| \hat{w}(k-1)$$

- update the error covariance

$$P\hat{w}(k) = (I - K\hat{w}(k)H(k))P\hat{w}(k)$$

Now we have EKFs for estimating both the states x, and the weights w, resulting in a pair of dual extended Kalman filters (DEKF) run in parallel. At each time step, the current estimate of x is used by the weight filter, and the current estimate of w is used by the state filter. For finite data sets, the algorithm is run iteratively over the data until the weights converge.

1. Noise Estimation:

The wireless channel conditions changes rapidly with the passage of time. We need to estimate the noise which were embedded in the desired image signal *d(k)*. The estimation of this noise is achieved by configuring System Identification with RLS & EKF algorithm iteratively as shown in *Fig. 3(A)*. This technique is used for modeling of an unknown system. The same input image *x(k)* is excited from both unknown system and adaptive algorithm. *d(k)* shows the desired image of unknown system shown by *Eq. 7*, $n_1(k)$ represents the observed noise, it degrades desired signal at the output of unknown system.

$$d(k) = x(k) + n_1(k) \qquad (7)$$

$$e(k) = d(k) - y(k) \qquad (8)$$

Where, *y(k)* is the adaptive filter output and difference between *d(k)* and *y(k)* gives error signal written in *Eq.8* The filter coefficients are represented by *w(k)*. These Coefficients are being regulated in order to reduce the error iteratively. When objective function is minimized, then the coefficients of adaptive filter are matched with that of unknown noise[11].

2. Image De-noising:

After achieving the estimated noise, image de-noising is done by means of Signal Enhancement configured with RLS & EKF algorithm shown in *Fig. 3(B)*. The embedded noise $n_1(k)$ are efficiently removed from desired image signal *x(k)* by correlating with estimated noise *e(k)*. The signal enhancement scheme has two input signals [9]. Thedesired image signal is contaminated with Gaussian noise represented by, $x(k)+n_1(k)$. The estimated noise *e(k)* is treated as the input of RLS & EKF adaptive algorithm, which is uncorrelated with *x(k)* but correlated with $n_1(k)$. The error signal is written in *Eq. 9*.

$$e(k) = x(k) + n_1(k) - y(k) \qquad (9)$$

The main function of this configuration is to provide a system output feedback to the adaptive filter and then modifying the filter by using RLS & EKF adaptive algorithm in order to achieve the least square estimate [6 11].

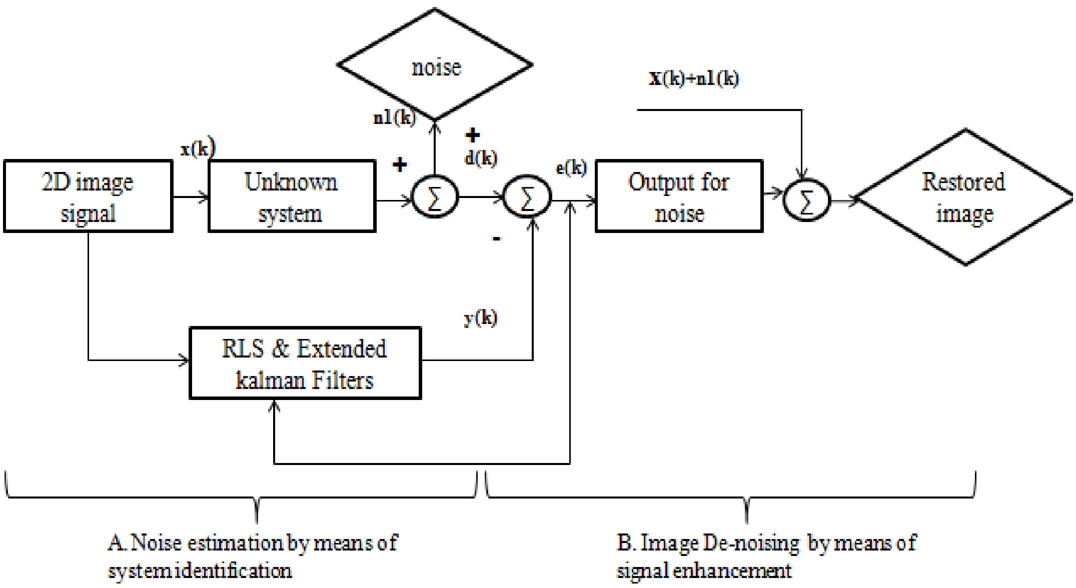


Figure.3: RLS & EKF methodology for Image restoration

III. SIMULATION RESULTS & ANALYSIS

	Gaussian noise image restoration by			salt & pepper noise image restoration by			speckle noise image restoration by		
Parameters	Wiener	RLS	Kalman	Wiener	RLS	Kalman	Wiener	RLS	Kalman
MSE	0.1591	0.1363	0.0906	0.4496	0.1428	0.0022	0.0389	0.0019	0.1060
PSNR	56.2814	56.7843	81.1848	51.6025	56.5838	74.6891	62.2330	75.3490	80.5054
SSIM	0.9816	0.9816	1.0000	0.9888	0.9910	0.9999	0.9993	0.9998	0.9999
FSIM	0.9493	0.9882	0.9994	0.8616	0.9265	0.9895	0.9736	0.9993	0.9998
VIF	0.1470	0.2816	0.7996	0.0035	0.0494	0.7018	0.0927	0.6683	0.7913
IQI	0.2855	0.3754	0.9908	0.0627	0.2694	0.9576	0.5950	0.9609	0.9881

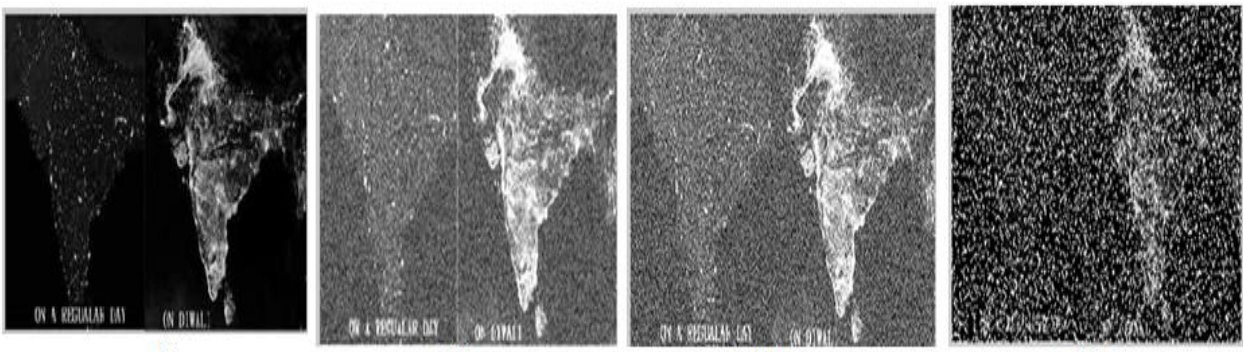
In this paper, the methodology for image restoration, is tested and implemented in MATLAB R2012.a software by acquiring the original gray scale data- based satellite images. This benchmark consists of subjective, objective and graphical measures for the evaluation of image quality. The subjective criterion is done by means of Human Visual System (HVS) and provides less precision. The objective criterion is done by means of result analysis quality metrics.

A. Image Restoration results for different noises using Wiener, RLS, EKF algorithms

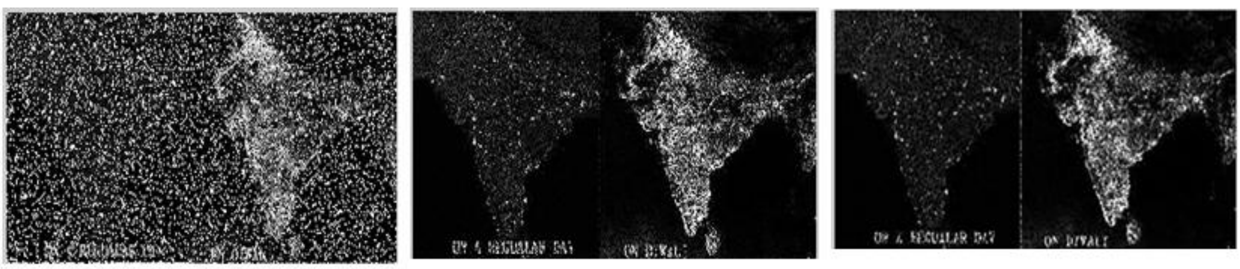
Fig. 4(a), 5(a), 6(a) represents the data-based satellite image as an input. These images are corrupted by adding Gaussian noise, impulse noise and speckle noise power as shown in *Fig. 4(b), 4(d), 4(f); 5(b), 5(d), 5(f) and 6(b), 6(d), 6(f)* respectively. The important parameters of wiener, RLS, EKF adaptive algorithm are required to select through consecutive testing, i.e. forgetting factor, $\lambda = 0.98$; filter coefficients = 2; regularization factor, $\delta = 0.001$. The satellite image restoration is achieved from wiener, RLS, EKF adaptive algorithm shown in *Fig. 4(c), 4(e), 4(g); 5(c), 5(e), 5(g) and 6(c), 6(e), 6(f).* Table 1 shows the quantitative parameters, i.e. MSE, PSNR, SSIM, FSIM, VIF, & IQI are computed for the performance evaluation of RLS, & EKF adaptive restoration. The noise level for each stage is calculated by means of MSE and the retrieved image quality is examined by PSNR. In this paper, the overall behavior of our methodology validates that the noise level is successively diminished by improving the values of PSNR and the values for MSE are minimized effectively during the whole process.Obtained results for image restoration using Wiener, RLS and dual extended kalman filter algorithms are given below.

Table 1: comparison of wiener, RLS, EKF algorithms based on parameters for satellite restored images

Wiener Filter Results for Satellite Image:



(a) (b) (c) (d)



(e) (f) (g)

Figure.4: satellite images (a) original image (b) Gaussian noisy image (c) Gaussian noise restored image (d) Salt & pepper noise image (e) salt & pepper noise restored image (f) speckle noise image (g) Speckle noise restored image

RLS Filter Results for Satellite Image:

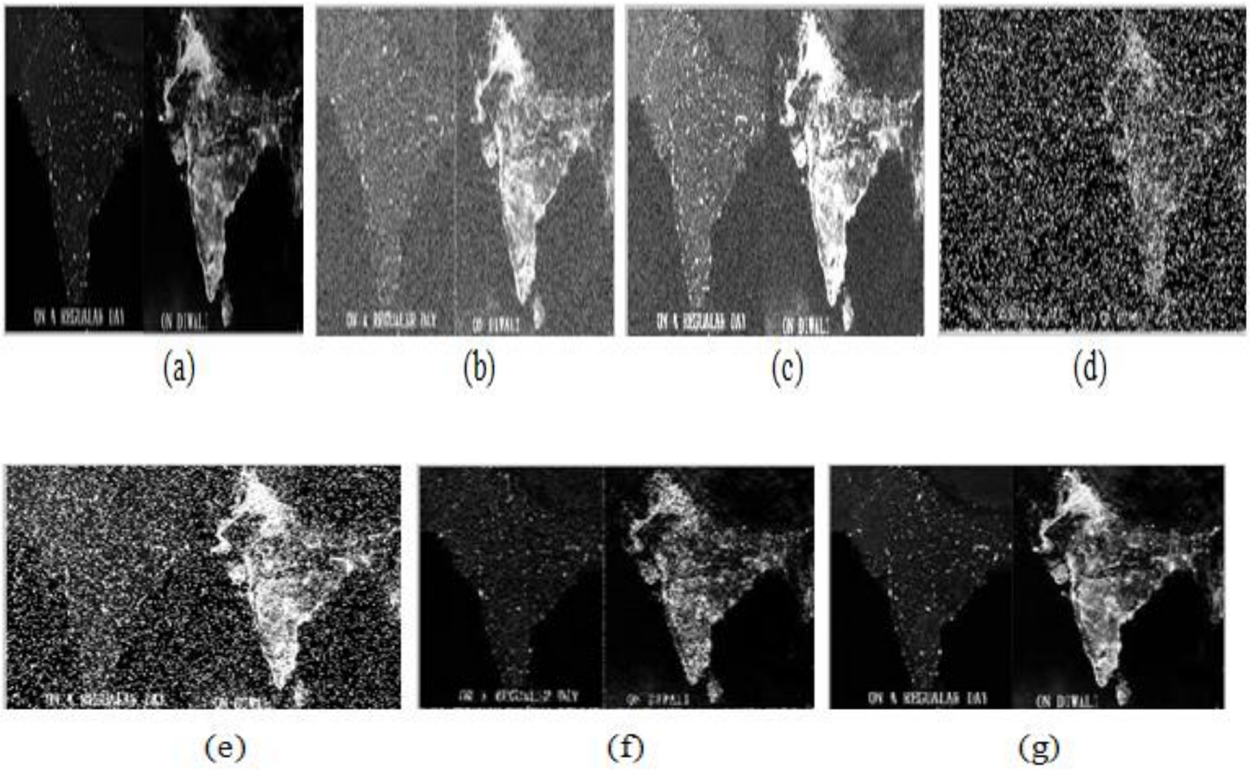


Figure.5: satellite images (a) original image (b) Gaussian noisy image (c) Gaussian noise restored image (d) Salt & pepper noise image (e) salt & pepper noise restored image (f) speckle noise image (g) Speckle noise restored image

Kalman filter Results for satellite image:

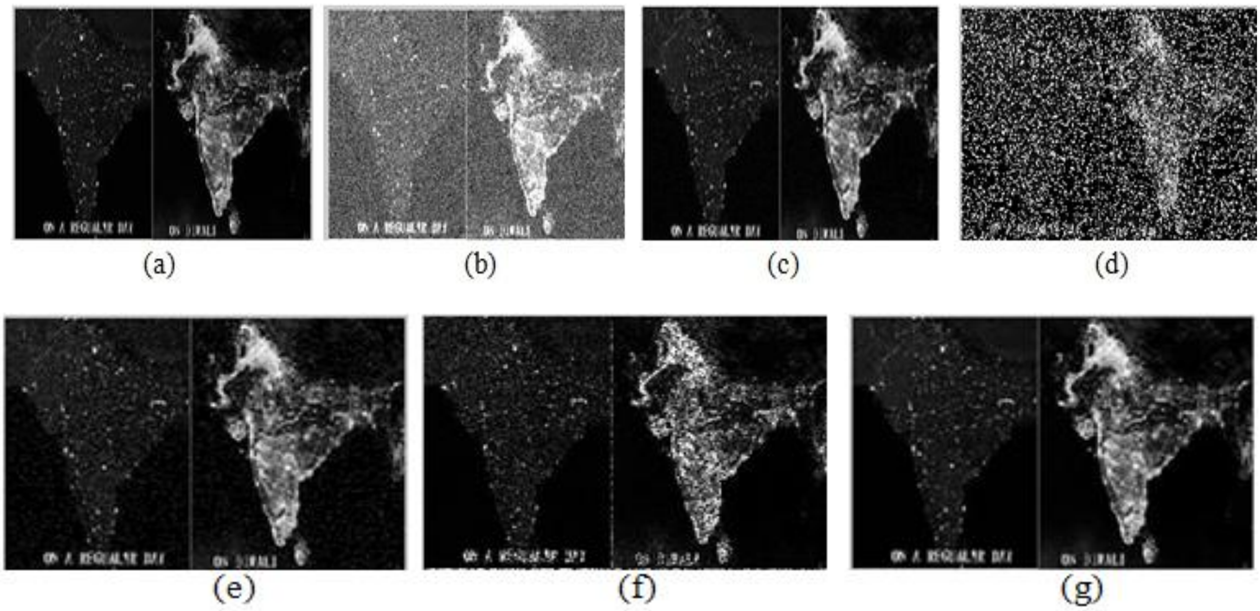


Figure.6: satellite images (a) original image (b) Gaussian noisy image (c) Gaussian noise restored image (d) Salt & pepper noise image (e) salt & pepper noise restored image (f) speckle noise image (g) Speckle noise restored image

B. Quality Metrics:

In this section we describe various objective image quality metrics to assess the quality of different image restoration strategies. Generally there are three kinds of objective image quality metrics are available:

Full Reference (FR)

In this paper, we consider Full Reference quality metrics to assess the quality of an image. The below table 2 represents the list of quality metrics that are used in this work.

Table 2: Performance Metric analysis:

S. No	Metric	Acronym	Abbreviation	Ref.	Description
1	FR	MSE	Mean Square Error	[12]	$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[f(x,y) - \hat{f}(x,y)]^2$
2	FR	PSNR	Peak Signal-to-Noise Ratio	[13]	$\mathrm{PSNR} = 10\log_{10}\left({255^2}/{\mathrm{MSE}}\right)$
3	FR	SSIM	Structural Similarity Index	[12]	$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{({\mu_x}^2{\mu_y}^2 + c_1)(\sigma_x\sigma_y + c_1)}$
4	FR	FSIM	Feature Similarity Index Metric	[14]	See [14]
5	FR	VIF	Visual Information Fidelity	[15]	See [15]
6	FR	IQI	Image Quality Index	[16]	See [16]

Table 3: Performance analysis of image restoration techniques based on PSNR (in dB) for different noises.

	Satellite Image with Gaussian noise restored by			Satellite image with salt & pepper noise restored by			Satellite image with speckle noise restored by		
variance	Wiener	RLS	EKF	Wiener	RLS	EKF	Wiener	RLS	EKF
0.01	64.4001	73.0209	81.3166	66.0439	76.0678	82.0384	72.4175	100.104	82.531
0.02	64.1969	71.7539	80.5715	63.0749	72.2835	81.4228	71.2161	95.856	82.5114
0.03	63.8311	70.8132	78.2131	61.5494	69.7057	80.9929	70.2697	93.1431	82.1036
0.04	63.5211	69.956	80.8924	60.3747	67.8294	80.4893	69.4971	91.1483	82.3611
0.05	63.311	68.9793	81.1657	59.5394	66.4521	80.0964	68.9474	88.1351	82.0721
0.06	63.0282	68.2832	79.7875	58.8086	65.4563	79.8053	68.2086	87.0686	82.3024
0.07	62.7788	67.6082	81.219	58.1363	64.6602	67.5362	67.7896	88.1343	82.2166
0.08	62.5097	66.9944	81.0227	57.5674	63.846	79.1685	67.4346	86.0292	81.6127
0.09	62.2307	66.2988	81.3887	57.145	63.1861	78.8808	67.0267	84.983	81.7549

Here are comparing wiener, RLS, EKF algorithms based on PSNR (in dB) of restored images & which are corrupted by Gaussian, salt & pepper & speckle noises. In figure (7),(8),(9) we can observe that EKF gives the efficient restoration than the wiener & RLS algorithms. EKF algorithm offering more computational requirements but with the cost of complex computations EKF gives the better PSNR. In today's more complex computations also solved easily with the advanced processors. These algorithms applied on many real time images, medical images for restoration but here we presented only satellite image restoration results. From all the observations algorithms EKF giving the efficient restoration for images which are corrupted by the Gaussian, salt & pepper noises.

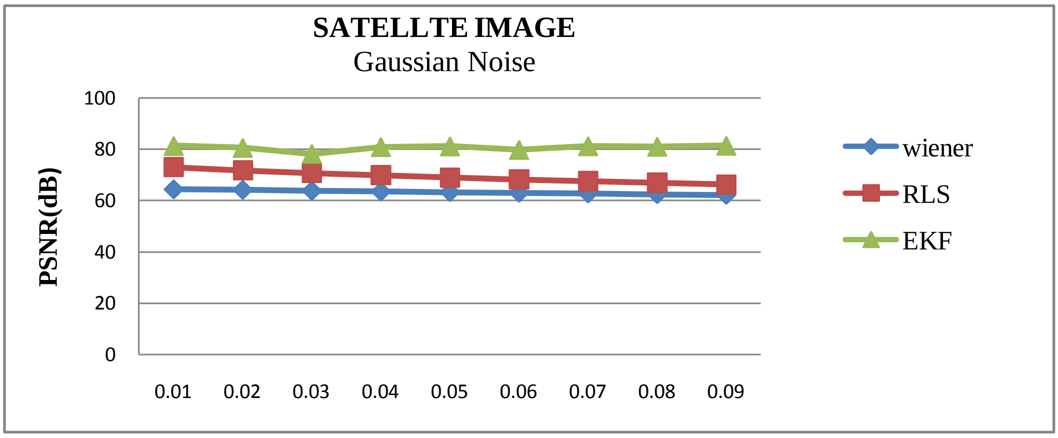


Figure.7: Comparison Chart of PSNR (in dB) of different adaptive filters for satellite Image Corrupted by Gaussian Noise

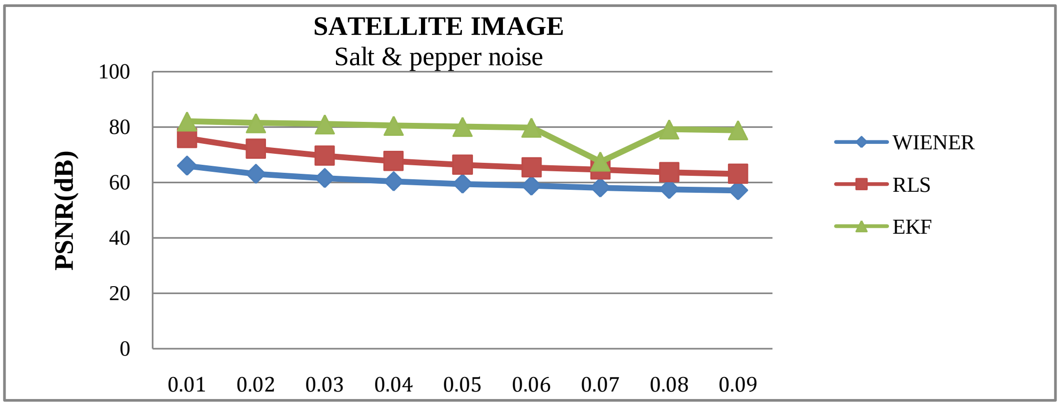


Figure.8: Comparison Chart of PSNR (in dB) of different adaptive filters for satellite Image Corrupted by Salt & pepper Noise.

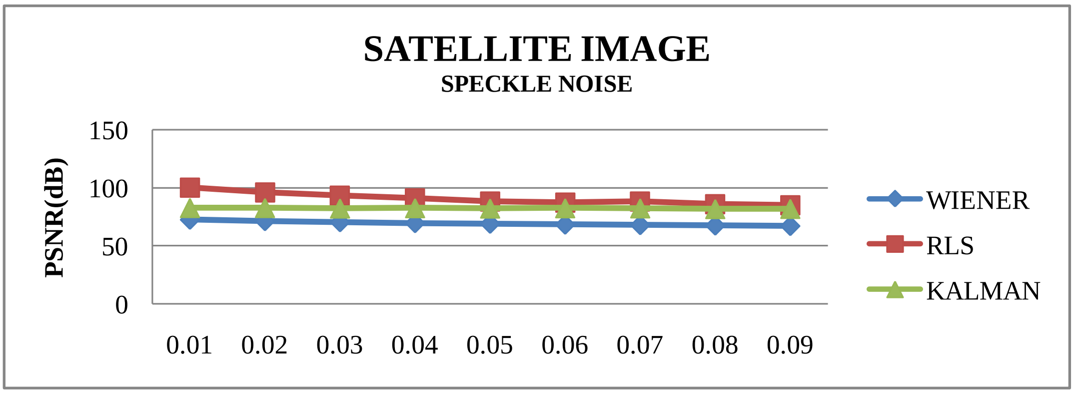


Figure.9: Comparison Chart of PSNR (in dB) of different adaptive filters for satellite Image Corrupted by Speckle Noise

CONCLUSION

Image restoration is performed based on adaptive techniques. Wiener, RLS and EKF filters are successfully implemented and results are verified. Those algorithms performance is evaluated by means of human visual system, quantitative measures in terms of MSE, PSNR, SSIM, FSIM, VIF, & IQI and by graphical measures. Visually both RLS, EKF adaptive algorithms gives better restored images. but we observed that for the different types of images (satellite, real time, medical images)are contaminated by the noises like Gaussian, salt & pepper and speckle noise images are efficiently restored by the EKF filter than the RLS algorithm but for the speckle noise images EKF filter gives poor performance metrics.Here are comparing wiener, RLS, EKF algorithms based on PSNR (in dB) of restored images & which are corrupted by Gaussian, salt & pepper & speckle noises. In figure (7),(8),(9) we can observe that EKF gives the efficient restoration than the wiener & RLS algorithms. EKF algorithm offering more computational requirements but with the cost of complex computations EKF gives the better PSNR.From all the observations algorithms EKF giving the efficient restoration for images which are corrupted by the Gaussian, salt & pepper noises.Finally in this project EKF filter gives better results in parametric wise compared to the wiener and RLS algorithms.

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