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RESEARCH ARTICLE

A PROPOSED APPROACH FOR IMAGE DE-NOISING

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ABSTRACT

The search for efficient image de-noising methods still is a valid challenge, at the crossing of functional analysis and statistics. In spite of the sophistication of the recently proposed methods, most algorithms have not yet attained a desirable level of applicability. All show an outstanding performance when the image model corresponds to the algorithm assumptions, but fail in general and create artifacts or remove image structures. The main focus of this dissertation is first to define an algorithm and based on that a non-linear adaptive filter is described which not only preserve the actual image structures in the presence of different types of noises (Salt & peppers &Zero-Mean Gaussian White Noise) as well as it provide better PSNR, MSE & MAE than other classic algorithms (Mean, Kaun, Fourth order differential) which will be clearly shown in result section.

INTRODUCTION

Ease of use and cost effectiveness has contributed to the growing popularity of digital imaging systems. However, inferior spatial resolution with respect to traditional film cameras is still a drawback.As a cost efficient alternate, image processing methods have been exploited through the years to improve the quality of digital images. Uncompressed pictures or video require very high data rates. The transmission or storage of this data may be impractical, or even impossible for many applications. However, there is significant redundancy both in video and pictures, allowing compression of data. Yet, compression ratios above a certain level are achieved at the expense of some loss of detail in the image or video. The amount of compression is determined by the bandwidth requirements for the particular application.

Image enhancement

These are used to highlight certain features of interest in an image. Two important examples of image enhancement are:To increasing the contrast level, and Changing the brightness level of an image so that the image looks better. Depending on applications, there are various types of imaging systems. X-ray, Gamma ray, ultraviolet, and ultrasonic imaging systems are used in biomedical instrumentation.

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In astronomy, the ultraviolet, infrared and radio imaging systems are used. Sonic imaging is performed for geological exploration. Microwave imaging is employed for radar applications. But, the most commonly known imaging systems are visible light imaging. Such systems are employed for applications like remote sensing, microscopy, measurements, consumer electronics, entertainment electronics, etc. Noise in an image is a very common problem. An image gets corrupted with different types of noise during the processes of acquisition, transmission/ reception, and storage/ retrieval. Noise may be classified as substitutive noise (*impulsive noise: e.g., salt & pepper noise, random-valued impulse noise, etc.*) and additive noise (*e.g., additive white Gaussian noise*). The impulse noise of low and moderate noise densities can be removed easily by simple denoising schemes available in the literature. The simple median filter [1,3,8] works very nicely for suppressing impulse noise of low density. However, now-a-days, many de-noising schemes [21] are proposed which are efficient in suppressing impulse noise of moderate and high noise densities.

Literature Survey

Rachana Dhannawat et al. (2016) authors proposed a novel technique for blind image de-noising using SVD and local pixel grouping. The technique is checked against salt & pepper noise and Gaussian noise for grey as well as colour images and compared with state of art algorithm LPGPCA. Authors found that the proposed technique gives better results when compared using objective criteria. Yali Liu (2015) performed image de-noising using wavelet transform and the genetic algorithm.

These two methods are used to estimate the de-noising results. Experimental results show the validity of the new algorithm with the comparison of existing techniques.Bhawna et al. (2015) presented practical aspects of various types of filters that have been used for suppression of noise.Firas Ajil Jassimproposeda novel approach to suppress noise from the image is conducted by applying the interquartile range (IQR) which is one of the statistical methods used to detect outlier effect from a dataset. Gabriela Ghimpeteanuconsider an image decomposition model that provides a novel framework for image de-noising. The strategy which is developed by authors to de-noise the components of the image in the moving frame in order to preserve its local geometry, which would have been more affected if processing the image directly. Malini et al. **(**2015**)** claims that in de-noising problems signal and noise can be separated in the process and hence elimination of noise becomes easier. EnmingLuo et al. (2016**)** [7] proposed an adaptive learning procedure to learn patch-based image priors for image de-noising. [Rahul Singh et al., 2015] Rahul Singh et al. discussed the various image de-noising techniques.In this paper authors try to attempt at the revision of the research publications put forward in the recent past. Papers addressing various different image de-noising techniques have been scrutinized & their essence has been summarized. SmritiSrivastava et al. defined that image de-noising is the process of removing blurring artifacts from an image that may be caused by atmospheric disturbances, camera misfocus or motion blur. Authors claimed that Median filters when applied over the complete image causes a change in the pixel intensities and also modifies the value of the unaffected pixels. Dhanushree.V et al. authors proposed a median filter and adaptive wavelet thresholding shrinkage technique for image de-noising.measured in terms of the PSNR and is observed that the proposed method obtains better PSNR compared to existing method.Vandana Roy et al. (2013) presented a review on various filters of image de-noising. P.Charishma Reddy et al. implemented the survey of Lazy window for SIMD Architectures and Histogram-Based Bilateral Filtering (BF). Rajni et al. (2014) presented a survey of digital image de-noising approaches. As images are very important in each and every field so, Image De-noising is an important pre-processing task before further processing of image like segmentation, feature extraction, texture analysis etc. authors survey showed the different type of noises that can corrupt the image and different type of filters which are used to improve the noisy image. RohitJaspal et al**.** authors proposed a novel method for image de-noising which performs better than the other recently proposed de-noising methods for MRI.

Proposed Approach

The detailed algorithm for the (Proposed) Adaptive median filter is given as follows. Assume D (i, j) is a moving window centred at pixel $d(i, j)$ with a window size of $2k + 1$ (where k is an integer). In this case, the window size is equal in both dimensions and has to be an odd number, such as 3, 5, 7, etc. To calculate the local mean and local standard deviation, it is necessary to first obtain the sum $S(i, j)$ of all the $N(i,j)$ pixel values in the moving window.

$$S(i,j) = \sum_{m=i-k}^{i+k} \sum_{n=i-k}^{j+k} d(m,n)$$

$$N(i,j) = (2k+1)^2$$

The local mean $\mu(i, j)$ of the moving window D is then computed as:

$$\mu(i,j) = \frac{S(i,j)}{N(i,j)}$$

and the local standard deviation $\sigma(i, j)$ is calculated as

$$\sigma(i,j) = \frac{\sqrt{\sum_{m=i-k}^{i+k}\sum_{n=i-k}^{i+k}(d(i,j)-\mu(i,j))^2}}{N(i,j)}$$

The range of valid pixel values can thus be determined by the above local statistics and a user-defined multiplier M. The lower bound $LB(i, j)$ and upper bound $UB(i, j)$ are defined as

$$LB(i,j) = \mu(i,j) - M\,\sigma(i,j)$$

$$UB(i,j) = \mu(i,j) + M\,\sigma(i,j)$$

Valid pixels and speckle are then identified and labelled in a separate mask with moving window L centered at $l(i, j)$. For every pixel $l(m, n)$

$$l(m,n) = 0 \text{ if } d(m,n) < LB(i,j) \text{ or } d(m,n) > UB(i,j)$$

$$l(m,n) = 1 \text{ if } LB(i,j) \le d(m,n) \le UB(i,j)$$

where$i - k \le m$, $n \le i + k$, 0 indicates speckle noise, and 1 a valid pixel. It is important to note that a non-central pixel outside the range in the current moving window may not be a speckle in another moving window centered on it. If the central pixel $l(i, j)$ at the mask moving window L equals 0 (i.e., labeled as speckle), then only the original central pixel value $d(i, j)$ is replaced by the local adaptive median $r(i, j)$ of the local window, which is the median of all the values of the pixels that are labeled as valid, excluding speckle pixels. The local adaptive median $r(i,j)$ is calculated as:

$r(i, j)$ = median $(d(m, n))$

where

$l(m, n) = 1$ and $i - k \le m$, $n \le i + k$.

RESULTS AND DISCUSSION

The proposed algorithm is tested on various standard images (Namely Lena & Pentagon). The algorithm is applied using various performance indices (namely MSE, MAE and PSNR) at different values & types of noises. Along with these comparative studies are represented in this chapter.

PSNR (in db) Vs Noise Variance (Sigma) of Salt & Peepers Noise for Lena (512x512) image

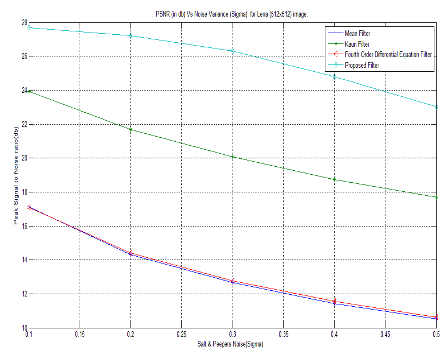

Figure 4.1. Relationship between PSNR and sigma for Salt & Peepers Noise of Lena Image

RMSE Vs Noise Variance (Sigma) of Salt & Peepers Noise for Lena (512x512) image

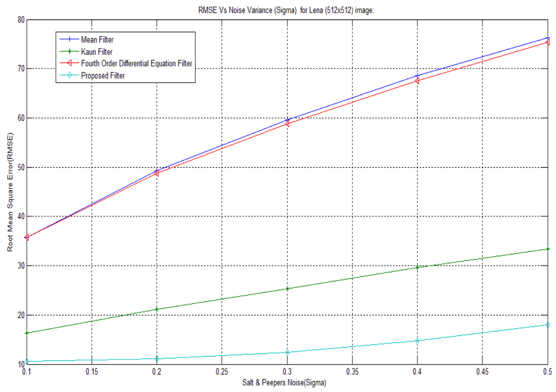

Figure 4.2. Relationship between RMSE and σ for Salt and Pepper noise for lena image

4.3 MAE Vs Noise Variance (Sigma) of Salt & Peepers Noise for Lena (512x512) image

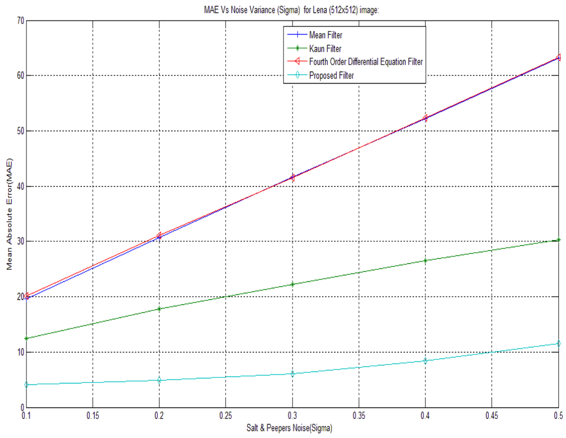

Figure 4.3: Relationship between MAE and σ for Salt & Peepers Noise of Lena Image

4.4 PSNR (in db) Vs Noise Variance (Sigma) of Zero-Mean Gaussian White Noise for Lena (512x512) image

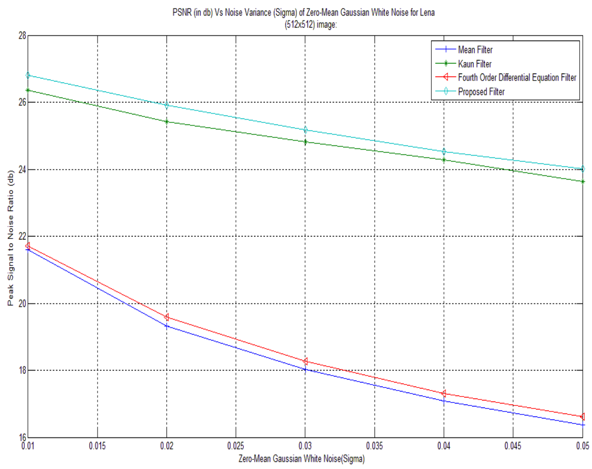

Figure 4.4: Relationship between PSNR and σ For Zero Mean white Gaussian Noise of Lena Image

4.5 RSME (in db) Vs Noise Variance (Sigma) of Zero-Mean Gaussian White Noise for Lena image

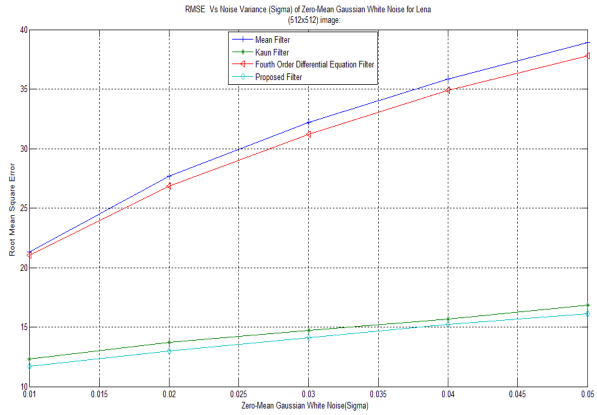

Figure 4.5 Relationship between RSME and sigma for Zero Mean White Gaussian Noise of Lena Image

4.6 MAE Vs Noise Variance (Sigma) of Zero-Mean Gaussian White Noise for Lena (512x512) image

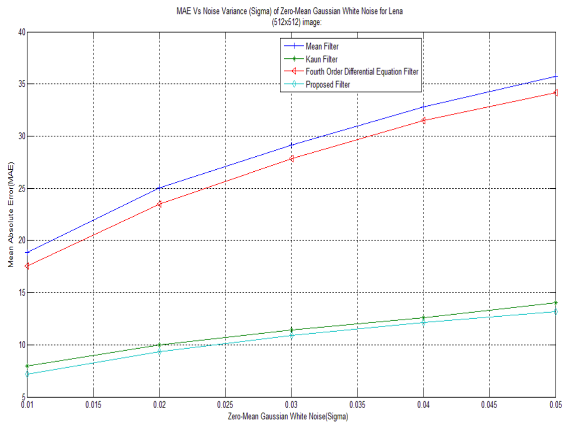

Figure 4.6. Relationship between MAE and σ for Zero-Mean Gaussian White Noiseof Lena Image

4.7 PSNR Vs Noise Variance (Sigma) of Salt & Peepers Noise for Pentagon (512x512) image

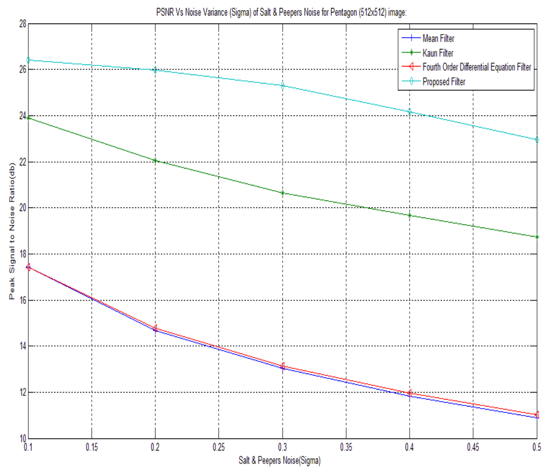

Figure 4.7: Relationship between PSNR and σ for Salt & Peppers Noise of Pentagon Image

4.8 RMSE Vs Noise Variance (Sigma) of Salt & pepper noise for Pentagon image

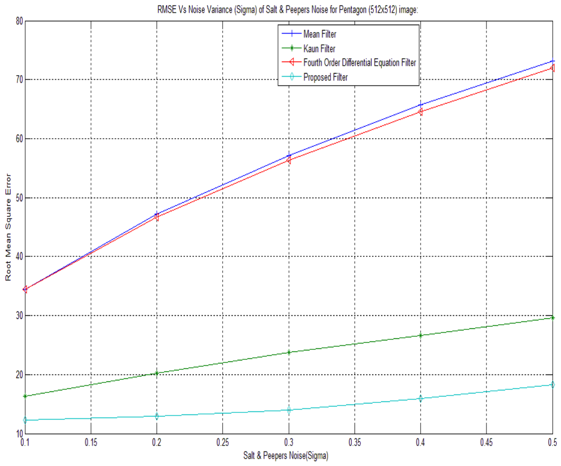

Figure 4.8: Relationship between RMSE and σ for salt & pepper Noise of Pentagon Image

4.9 MAE Vs Noise Variance (Sigma) of Salt & Peepers Noise for Pentagon (512x512) image

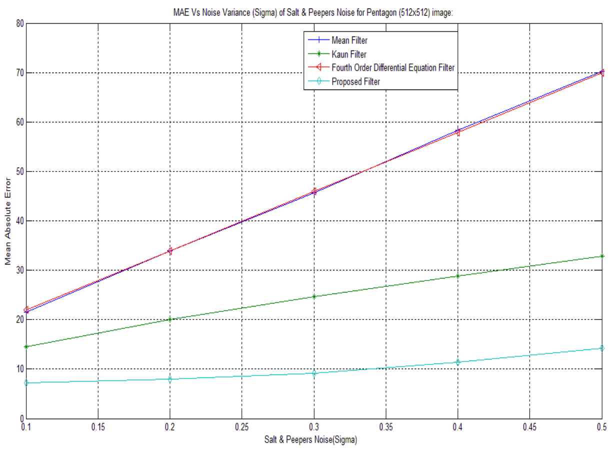

Figure 4.9: Relationship between MAE and σ for salt & pepper Noise of Pentagon Image

4.10 PSNR (in db) Vs Noise Variance (Sigma) of Zero-Mean Gaussian White Noise for Pentagon image

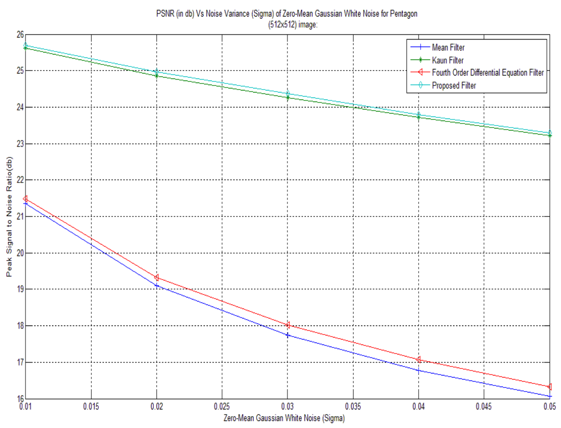

Figure 4.10. Relationship between PSNR and σ for Zero Mean white Gaussian Noise of Pentagon Image

4.11 RMSE Vs Noise Variance (Sigma) of Zero-Mean Gaussian White Noise for Pentagon image

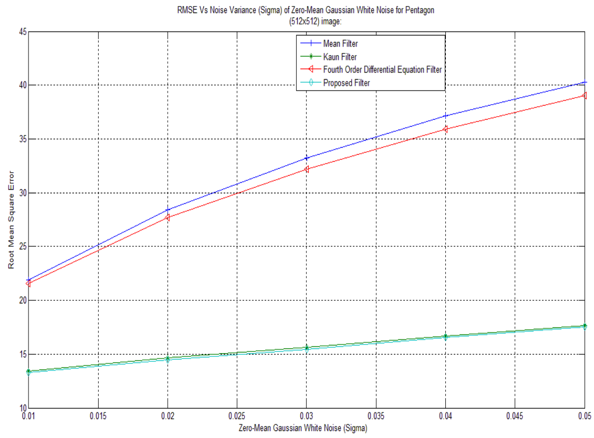

Figure 4.11: Relationship between RMSE and σ for zero mean white Gaussian noise of pentagon image

MAE Vs Noise Variance (Sigma) of Zero-Mean Gaussian White Noise for Pentagon (512x512) image

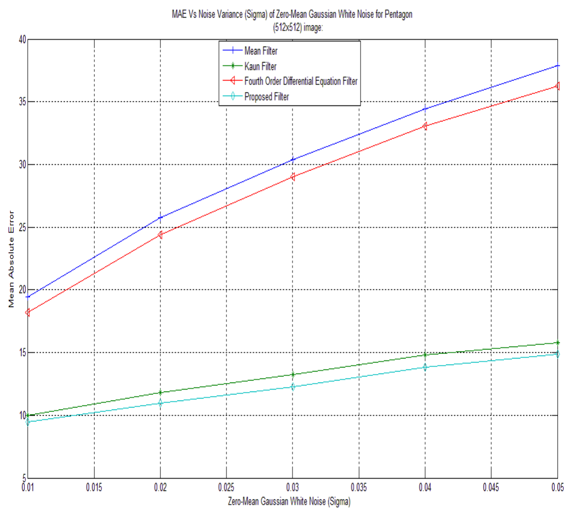

Figure 4.12: Relationship between MAE and σ for Zero-Mean Gaussian White Noise of Pentagon Image

The above figures shows the relationship between PSNR and Standard deviation(σ), RSME and Standard deviation ,MAE and Standard deviation of Lena Image using Mean Filter (blue), Kuan Method (green), Fourth order diff filter(red) and Proposed Method (sky blue).It is very clear from the plot that there is increase in PSNR value of image, decrease in RSME value of image and decrease in MAE value of image with the use of proposed method over other methods. This decrease represents improvement in the objective quality of the image. The above figures shows the relationship between PSNR and Standard deviation(σ), RSME and Standard deviation ,MAE and Standard deviation of Lena Image using Mean Filter (blue), Kuan Method (green), Fourth order diff filter(red) and Proposed Method (sky blue).It is very clear from the plot that there is increase in PSNR value of image, decrease in RSME value of image and decrease in MAE value of image with the use of proposed method over other methods. This decrease represents improvement in the objective quality of the image.

Table 4.1: Performance of the proposed algorithms for various noisy images: Comparison of proposed Algorithm with other Algorithms on the basis of PSNR, RMSE& MAE indices

For Lena with Salt & Pepper Noise

Sr. No	Noise Variance (σ)	Mean Filter				Kuan Filter				Fourth Order Diff Equation				Proposed			
		PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity
1	0.1	17.108	35.710	19.679	1.508965	23.924	16.293	12.430	20.765558	17.093	35.776	20.199	2.667591	27.672	10.582	4.0866	2.575543
2	0.2	14.303	49.326	30.700	1.227709	21.674	21.112	17.842	20.822755	14.408	48.733	31.134	2.545446	27.204	11.169	4.9002	2.551375
3	0.3	12.661	59.589	41.620	1.261195	20.074	25.381	22.232	21.256631	12.765	58.880	41.558	2.583917	26.318	12.368	6.1203	2.606459
4	0.4	11.434	68.626	52.247	1.235194	18.748	29.568	26.543	23.109376	11.568	67.582	52.289	3.26972	24.800	14.731	8.4468	2.898575
5	0.5	10.518	76.261	63.14	1.250572	17.679	33.441	30.296	22.402716	10.620	75.371	63.234	2.913144	23.023	18.073	11.577	2.635179

For Lena with Zero Mean Gaussian white Noise

Sr. No	Noise Variance (σ)	Mean Filter				Kuan Filter				Fourth Order Diff Equation				Proposed			
		PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity
1	0.01	21.591	21.314	18.855	1.272555	26.361	12.307	7.985	21.025368	21.709	21.026	17.544	2.647285	26.796	11.706	7.2019	2.585658
2	0.02	19.319	27.687	25.031	1.27907	25.429	13.701	9.9788	20.714691	19.585	26.850	23.460	2.603287	25.903	12.973	9.3252	2.645242
3	0.03	18.012	32.184	29.158	1.24149	24.809	14.714	11.435	21.055746	18.274	31.227	27.822	2.610485	25.173	14.111	10.896	2.584323
4	0.04	17.084	35.812	32.780	1.296053	24.273	15.651	12.601	23.635536	17.313	34.881	31.508	2.650339	24.524	15.206	12.159	2.801122
5	0.05	16.361	38.920	35.708	1.256676	23.636	16.842	14.006	21.788578	16.622	37.768	34.169	2.644813	24.018	16.117	13.167	2.643153

Table 4.2: Performance of the proposed algorithms for various noisy images: Comparison of proposed Algorithm with other Algorithms on the basis of PSNR, RMSE& MAE indices

For Pentagon with Salt & Peppers Noise

Sr. No	Noise Variance (σ)	Mean Filter				Kuan Filter				Fourth Order Diff Equation				Proposed			
		PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity
1	0.1	17.423	34.438	21.5392	1.424071	23.892	16.353	14.523	20.604797	17.426	34.429	21.986	2.510677	26.418	12.226	7.2127	2.791386
2	0.2	14.691	47.172	33.8554	1.262326	22.038	20.245	20.087	20.408205	14.776	46.711	33.822	2.581813	25.956	12.894	7.9292	2.589858
3	0.3	13.036	57.072	45.7274	1.296424	20.655	23.737	24.673	20.987863	13.150	56.327	46.003	2.587337	25.287	13.928	9.1246	2.554171
4	0.4	11.814	65.693	58.39	1.267728	19.679	26.561	28.835	21.901224	11.959	64.607	57.814	2.762378	24.154	15.867	11.337	2.630994
5	0.5	10.877	73.172	70.20	1.263914	18.744	29.580	32.922	22.114513	11.017	72.001	69.914	2.729903	22.953	18.221	14.271	2.590732

For Pentagon with Zero Mean Gaussian white Noise

Sr. No	Noise Variance (σ)	Mean Filter				Kuan Filter				Fourth Order Diff Equation				Proposed			
		PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity	PSNR	RMSE	MAE	Time complexity
1	0.01	21.356	21.899	19.416	1.258545	25.612	13.415	9.9704	20.612974	21.488	21.568	18.168	2.57006	25.69	13.296	9.4561	2.568969
2	0.02	19.101	28.390	25.744	1.280174	24.849	14.648	11.838	20.804066	19.316	27.694	24.387	2.527474	24.972	14.440	10.982	2.476464
3	0.03	17.734	33.228	30.409	1.259767	24.263	15.669	13.231	22.293296	18.015	32.171	29.038	2.80323	24.378	15.463	12.289	2.620532
4	0.04	16.771	37.126	34.404	1.292642	23.715	16.689	14.804	21.338988	17.061	35.905	33.035	2.743796	23.786	16.555	13.833	2.585069
5	0.05	16.061	40.287	37.909	1.346682	23.211	17.688	15.816	21.503046	16.331	39.053	36.263	2.653101	23.291	17.525	14.856	2.555896

The above figures shows the relationship between PSNR and Standard deviation(σ), RSME and Standard deviation ,MAE and Standard deviation of Lena Image using Mean Filter (blue), Kuan Method (green), Fourth order diff filter(red) and Proposed Method (sky blue).It is very clear from the plot that there is increase in PSNR value of image, decrease in RSME value of image and decrease in MAE value of image with the use of proposed method over other methods. This decrease represents improvement in the objective quality of the image. The above figures shows the relationship between PSNR and Standard deviation(σ), RSME and Standard deviation ,MAE and Standard deviation of Lena Image using Mean Filter (blue), Kuan Method (green), Fourth order diff filter(red) and Proposed Method (sky blue).It is very clear from the plot that there is increase in PSNR value of image, decrease in RSME value of image and decrease in MAE value of image with the use of proposed method over other methods. This decrease represents improvement in the objective quality of the image.

Conlusion & Future scope

In this, mid-term report, various spatial-domain filters for suppression of salt and peppers noise &Zero-Mean Gaussian White Noise (AWGN), available in literature, are studied and their performances are analyzed. Considering the limitations of the existing filters, efforts have been made to develop a spatial-domain filter.The performances of the proposed filter are compared with existing spatial-domain filters. The developed filter is compared against some well-known filters available in literature. The proposed spatial-domain filter is simulated on test images: Lena, Pentagon of sizes 512×512 pixels each corrupted with salt and peppers noise of standard deviation σ= 0.1,0.2,0.3,0.4 & 0.5 as well as Zero-Mean Gaussian White Noise (AWGN) of standard deviation σ= 0.01,0.02,0.03,0.04 & 0.05. To give a concise presentation of all simulation results so as to have a precise comparative study, the performance measures of the proposed filter as well as some high-performing existing filters are shown in Tables.In future we can extend our approach with the addition of more filters by using colour images instead of grey scale images.

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