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IMAGE RESTORATION BASED ON ENHANCED SWITCHED MEDIAN FILTER WITH NSSK

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ABSTRACT

This paper deals with an image restoration process, based on unsymmetrical high density impulse noise and Gaussian blur. By using these two different methods researcher first implemented an Enhanced switched median filter which is applied for denoising and second a Noise Suppressed Steering Kernel (NSSK) and median filter applied for deblurring. Even different methods are proposed for impulse noise, due to time complexity it has been replaced by switched median filter. To overcome the limitations in fuzzy filtering a switched median filter is proposed for obtaining a better performance on visual clarity and time in this proposed work. The proposed method is a hybrid method which employs an mixture of noise and blur .Different digital images are used to show the restoration results in terms of PSNR (dB) and visual effects which conforms better restoration through proposed method.

Keywords: image restoration, switched median filter, noise suppressed steering kernel (NSSK).

INTRODUCTION

Image restoration is one of the fundamental problems in image processing. 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 [1]. The various applications of image restoration are CCD camera, medical image, astronomy, satellite, remote sensing. While restoring a digital image which is corrupted by impulse noise some of the issues must be addressed, a) the quality of reconstructed image b) the computational efficiency of the method, c) different parameters applied on image.

In this part the researcher processed the past works which provide him clarity to perform his research. The review has performed on two variables one is denoising and another is deblurring. Deep insight has given to perform on impulse factor, that is salt and pepper noise which is quantized into two extreme values, which is either the minimum value, or maximum value the impulse noise takes either intensity 0 or L-1 [2]. The image is degraded with a combination of noise and blur. Noise occurs in the images when the pixels are randomly replaced by other values. A study is made on various Denoising and Deblurring methods. The median filters, when applied uniformly across the image, tend to modify both noisy as well as noise free pixels, resulting in blurred and distorted features [3]. To identify the presence of impulse noise a switched median filter is proposed, where it takes the difference of the median values of pixels in the filtering window and current pixel value is compared with a threshold value [4]. Another approach is followed by using a noise detector type in which the noise is detected by using an adaptive median filter [5]. A new median based on switching filter, which is termed as progressive switching median filter, where both the impulse detector and the noise filter are applied progressively in iterative manners [6]. The noisy pixels processed in the current iteration are used to help the process of the other pixels in the subsequent iterations. The removal of random valued noise is more difficult problem, because the differences in the gray levels between a noisy pixel and its noise free neighbour, will be of the times are less significant [7]. These limitations are overcome by using a modified progressive switched median filter is applied to image enhancement. A Noise Adaptive Soft Switching Median filter is used to achieve much improved filtering performance in terms of effectiveness in removing impulse noise while preserving signal details and robustness in combating noise density variations [8]. A Bilateral filtering overcomes the well-known blurring effects of a Gaussian filter and exhibits edge-preserving property, which is desirable for many image and video processing tasks [9]. Another type of image processing methods exploiting the self-similarity in natural image is emerging. It means that the higher level patterns, e.g., texton and pixon, will repeat themselves in the image [10]. A patch based frame work for image denoising through local geometric representations of an image that identifies the regions of similar structure and groups those together [11]. A dictionary for each cluster describes the patches in the cluster. Tschumperle proposed a common frame work for image restoration which is based on the iterative local diffusion in the image plane guided by the local structure tensor and treating image restoration as a regression task on the 2-D image plane [12]. An NLKR method is proposed for both the nonlocal self-similarity and local structural regularity properties in natural images and videos [9]. A noise suppressed steering kernel (NSSK) is proposed for deblurring and denoising which is an iterative process [13]. The presence of noise in spurious edges on iterative process gets added up and become stronger if not removed. A median filter is applied to overcome these issues [13]. Motion blur and defocus blur are common cause of image degradation [14]. Blind restoration of such images demands identification of the accurate point spread function for these blurs. The identification of joint blur parameters in barcode images is considered by using logarithmic power spectrum analysis.

This paper is aligned in such a way that, first part considerate on various filtering method for image restoration. The second part describes an overview on the previous work. The third part gives detailed information on improvement in the proposed work. The last section employs on experimental and comparison results.

OVERVIEW OF PREVIOUS WORK

The previous work is a hybrid method which is applied for high density impulse noise by using fuzzy Denoising. To remove the Gaussian blur a Noise Suppressed Steering Kernel (NSSK) [13] with Median Filter is applied. Image restoration is done for different applications, based on the requirement of the applications filtering methods are applied. A brief review is made for the proposed method. Initially steering kernel was applied directly for restoration of degraded images; there was an issue while this method is applied. The output image was suffered with the noise in the spurious edges it blurs the edges for each iteration and wrinkles like noise is added up for each iteration and becomes stronger if it is not removed. To overcome such limitations NSSK [13] method is proposed in my previous research. Even NSSK produced better performance with fuzzy denoising method. Since this method is an iterative process there were some limitations on *time*. This issue was taken in to a consideration a fuzzy filter was replaced by switched median filter to overcome such issues while denoising is done.

Algorithm 1: Denoising and deblurring

Step-1: Input a degraded image which is affected by high density impulse noise.

Step-2: Assign Fuzzy membership function for the degraded image.

Step-3: Noise is identified by using fuzzy membership function based on the criteria. This gives the mean, median, standard deviation.

Step-4: Denoising is done by calculating mean, median and standard deviation for the degraded image.

Step-5: A Noise Suppressed Steering Kernel (NSSK) and Median Filter is applied for deblurring

Step 6: Reconstructed output image.

IMAGE DENOISING USING FUZZY FILTER

Impulse noise is caused by errors in data transmission, generated in noisy sensors, communication channels', error during tile data capture from digital cameras. Fuzzy Denoising is a machine learning technique in recent trends of research. Fuzzy filters are categorized into two sub classes they are Fuzzy classical filters and Fuzzy filters. Fuzzy classical filters use fuzzy logic for impulse noise detection, reduction and median filter. Fuzzy filters are dependent on fuzzy logic and they do not have any connections with classical filters. Fuzzy filters are used to remove high impulse noise and Gaussian noise [19].

Algorithm 2: Fuzzy denoising[13]

Step-1: Input noisy image

Step-2: Select 3x3 windows with center element Pij as processing pixel.

Step-3: If the processing pixel is $0 \leq$ Pij ≤ 255, then there is no change in the selected 3X3 window.

Step-4: If All pixels 0's or 255's then the processing pixel is replaced my mean filtering, else continue Step 5:

Step-5: Now Generate fuzzy rules for the 3 X 3 matrixes, the rule is generated for 0^{th} pixel to 9^{th} pixel.

Step-6: Assign Fuzzy membership function.

Step-7: Based on the processing pixel compute mean, median and standard deviation.

Step-8: Retrieved Denoised image.

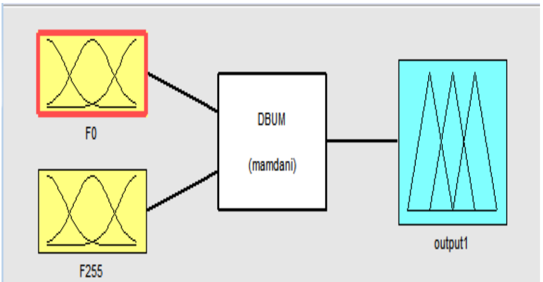

Figure-1. Fuzzy system [13].

Next we generate fuzzy rules for the 3 x 3 matrix. The rule is generated for 0^{th} pixel to 9^{th} pixel. From 0 to 4 we assign the membership function as small negative in which when the noise fall between 0 to 4 it assign as small negative. The next membership function takes the pixel value from 4 to 6, when the noise falls in this pixel it will consider as negative. When the noise fall on the pixel value from 6 to 9 it is named as large negative [13]. When fuzzy filter was applied for denoising it took much time to identify the noisy pixel based to the production rules and fuzzy member function. After processing each pixel mention in the step seven it took much time to decide and compute the mean, median, SD for denoising the image. To overcome such limitations a new switched median filter

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is proposed. The next section gives the detail description on the proposed method.

PROPOSED WORK

Image denoising using enhanced switched median filter

The proposed method is a hybrid method for denoising. Image and video restoration [9] is important field in image and video processing community, which aims to estimate the high-quality version of the low-quality observations that are typically noisy and of low resolution. For image denoising a fuzzy technique is used in my previous research.

The following mathematical equation is applied for the noise identification.

$$d(k,1) = |x(k,1) - x(i,j)| - N \leq k, 1 \leq N(1)$$

$$f = |\, d_{k,1} \pm t1 \,| \qquad \forall \qquad |\, d_{k,1} \pm t1 \,| \leq t2 \qquad (2)$$

$$S_{i,j} = \begin{cases} 0 \ if size(f) \leq t3 \\ 1 \ otherwise \end{cases}$$

For identification and processing of noisy pixel it takes much time and the fuzzy technique is replaced by switched median filter. The main purpose of this algorithm is to observe each and every pixel from the beginning till the end. The process begins by classifying the pixels into three different categories namely. Low intensity pixel, Medium intensity pixel, High intensity pixel. A 3X 3 window is with center pixel is considered and its adjacent pixels are checked. If the center pixel is not within the medium intensity range, then the entire pixel are considered to be corrupted. By finding the accurate boundary values we can get the accurate intensity range. To find whether the pixel is corrupted or not corrupted, the same process is applied to every pixel within the noisy image. As a result of this process a 2 dimensional map with values 0 and 1 alone is formed, where 0's indicate uncorrupted pixel and 1's indicate corrupted pixels. From the pixel centering the current pixel is grouped into three conditions. This is done by determining two boundaries B1 and B2for each pixel is processed. If $0 < X(i, j) < b1$, then the pixel will be assigned to lower intensity, otherwise to the medium intensity cluster for $b1 < X(i, j) < b2$, or to the high density cluster for $b2 < X(i, j) < 255$. The algorithm consists of two iterations. The first iteration involves checking for the presence of uncorrupted pixel by the usage of window of larger size. If it is checked for and there is no uncorrupted pixel, then there is no need for next iterations. The following mathematical equation is applied for the denoising.

$$M(i,j) = \mathrm{median}\{x(i-1,j-1), x(i,j-1), x(i-1,j+1), x(i-1,j)\}$$

$$d(i+k, j+1) = |\, x(i+k, j+1) - x(i, j) \,|$$

With $d(i+k, j+1) \neq (i, j)$

$$D(i, j) = \max\{d(i+k, j+1)\} \qquad (3)$$

$$F(i,j) = \begin{cases} 0: & D(i,j) < T1 \\ \dfrac{D(i,j) - T1}{T2 - T1} & : T1 \leq D(i,j) < T2 \\ 1: D(i,j) \geq T2 & \end{cases}$$

$$S_k = \{D_k - x(i, j)\} \qquad (4)$$

$$sum_k = sum(S_k).$$

$$L = \min(sum_k).$$

$$M(i, j) = \mathrm{median}\{L\} \qquad (5)$$

Repeat the equation (1) until the image gets converge.

Where x (i, j) is the Blur with Noise image and i, j are position of the image, M (i, j) is the median image, d (i, j) is difference of the neighboring pixel, D (i, j) is maximum of difference pixel F (i, j) is threshold mapped image, S_k is the difference of x (i, j) with maximum of difference pixel, where L reduce the window size. The various steps involved in the algorithm are given below.

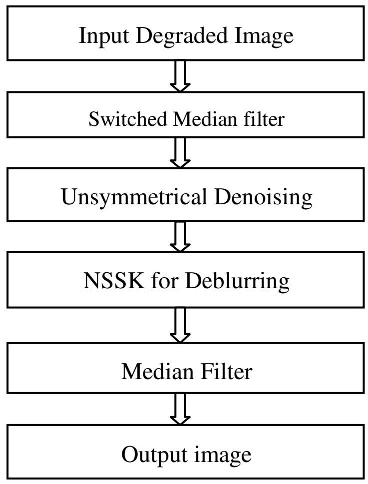

Figure-2. Block diagram for the proposed method.

Algorithm 3

Step-1: Consider a large sized window with center X (i, j). The center pixel must be the current pixel in the image.

Step-2: Arrange the pixels in ascending order and store it in an array *A* and find the median and store the result to *M*.

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Step-3: For every pair of adjacent pixels within the array A the intensity difference is calculated and the result is stored in the difference vector Ad.

Step-4: Find the pixels from Ad that corresponds to the maximum differences in the intervals of [0, M] and [M, 255]. Set these pixel's intensities as the decision boundaries B$1$and B2 respectively.

Step-5: If the processing pixel belongs to the middle cluster then it is classified as uncorrupted and process stops. Otherwise it must go for the second iteration, which will be invoked as follows.

Step-6: Impose a 3X3 window, being centered on the concerned pixel and repeat steps 2 to 4.

Step-7: If the current pixel belongs to the middle cluster, it is classified as "uncorrupted" pixel. Otherwise it is corrupted.

Step-8: Based on this algorithm we are updating the detection map. If the processing pixel is uncorrupted the detection map is updated with "0" otherwise detection map is updated with "1".

Step-9: Retrieved output image.

IMAGE DEBLURRING USING NOISE SUPPRESSED STEERING KERNEL (NSSK)

In image deblurring problem the degraded image is modeled as,

$$Y = h * x + n.$$

Where y is the degraded image, x is the unknown original image n is noise and h is point spread function of the blur operator and * denotes convolution. For blind and non-blind deblurring can be identified when finding x and h form y and for non-blind deblurring finding x form y and h are normally addressed by adopting a regularized expressing prior information about the image x and considering an objective function of the form [12].

The kernel regression framework defines its data model in 2-D as,

$$y_i = z(\mathrm{x}_i) + \varepsilon_i,\ i = 1, \cdots, P,\ \mathrm{x}_i = [x_{1i}, x_{2i}]^T, \quad (6)$$

The traditional process of steering kernel regression technique is a non parametric approach of regression which involves directly on the data itself instead of depending on any specific model. Classical parametric image processing methods rely on a specific model of the signal of interest and seek to compute the parameters of this model in the presence of noise [13]. With the relatively recent emergence of machine learning methods, kernel methods have become well-known and used frequently for pattern detection and discrimination problems [12]. The estimated smoothing matrices of the steering kernel regression method are data dependent, and, consequently, sensitive to the noise in the input image. Steering kernel regression is most effective when an iterative regression/denoising procedure is used to exploit the output (less noisy) image of each iteration to estimate the radiometric terms of the kernel in the next iteration [12]. The above method outputs suffer with spurious edges when noise is high. This limitation of the steering kernel is overcome by using median filters [13]. The presence of spurious edges on iterative process gets added up and becomes stronger if not removed. Hence it can be eliminated by using median filters at the end of the each iteration.

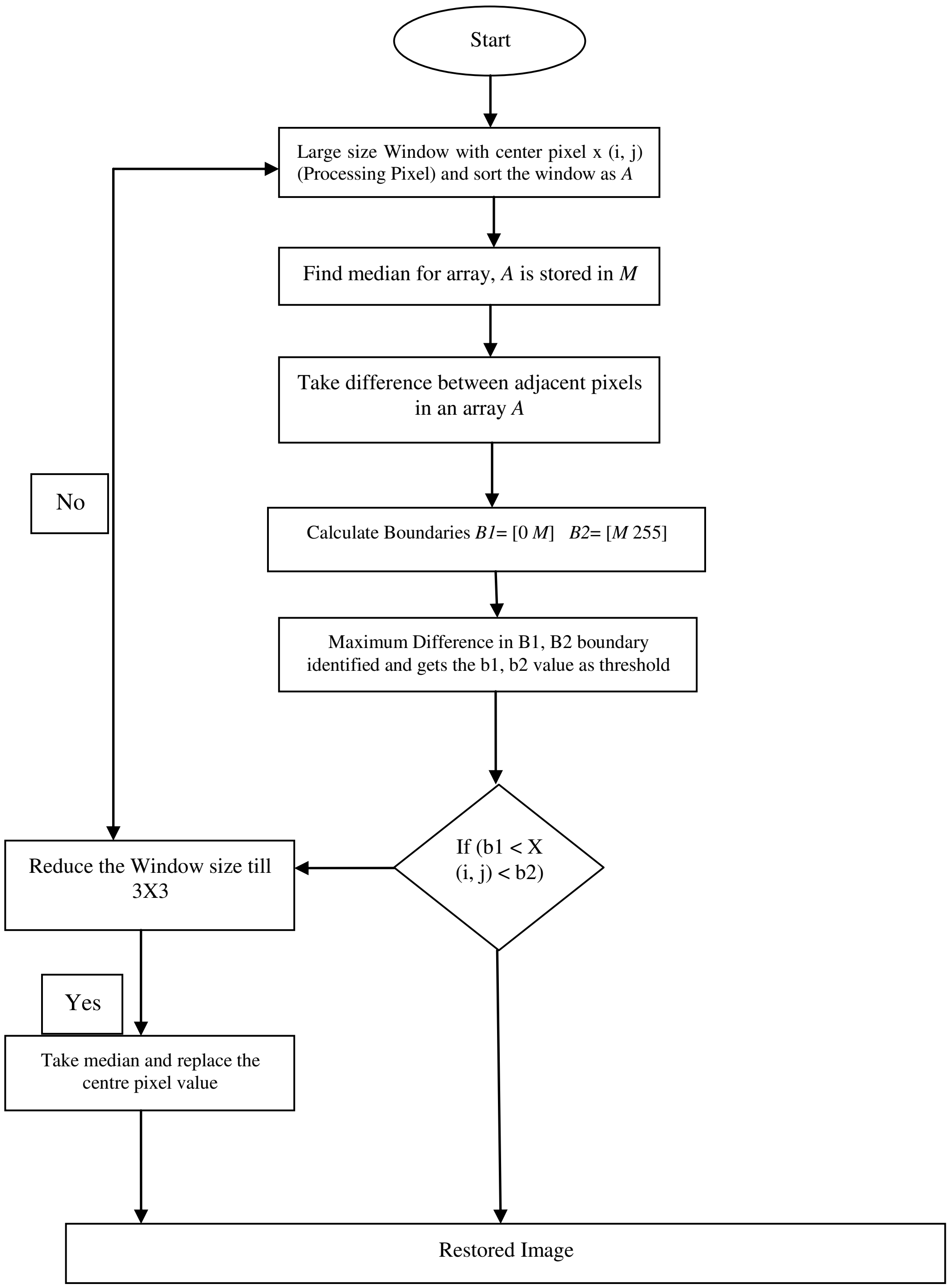

Figure-3. Flowchart for the proposed method.

Algorithm 4: NSSK Method on deblurring

Step-1: Input noisy image.

Step-2: Take a 3 X 3 window for processing.

Step-3: Formulate local gradients for the input image.

Step-4: Apply parametric analysis such as Scaling, Elongation and Rotation for the input image.

Step-5: Apply Steering matrix for the each iteration for the processing pixel.

Step-6: Now A locally adaptive deconvolution operator is applied.

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Step-7: Suppression of Spurious Edges is removed by using Median Filter.

Step-8: From the output value it is then taken to the threshold value.

Step-9: If the threshold value is met that will be the final output else it has to repeat the iteration until it meets the threshold value.

Step-10: Retrieved output image

This method has the following steps.
Formulating image and local gradient.

$$\nabla g = \frac{\partial g}{\partial x} * \bar{x} + \frac{\partial g}{\partial y} * \bar{y}$$

Where, $\frac{\partial g}{\partial x}$ is the gradient in x direction and $\frac{\partial g}{\partial y}$ is the gradient in y direction.

Parametric analysis.

Gradient of an image can be used to analyze various parameters such as scaling parameters, Rotational parameter and elongation parameter. Scaling parameters provide information on sizes of the image. [13] Rotational parameters are one associated with defining on what angle the image is been located or rotated. Elongation parameter is those which imply how the image has been elongated.

Steering matrix formation.

The measured data of steering kernel is represented as, $m_i = r(d_i) + \alpha_i$ where $i = 1 \ldots p$

Where, r (d_i) = regression function acting on pixel coordinates,

α_i = zero mean noise values distributed identically and
p = total number of pixels.

The steering kernel is mathematically represented as

$$SK(y_l - y_i) = \sqrt{\det(CV_l)} \exp\{-(y_l - y_i)^T CV_l (y_l - y_i)\}$$

Where, y_i= center pixel where steering kernel (SK) window is located,
y_l= locally selected pixel within SK window,
CV_l= Covariance matrix with window around y_l.

The final noise suppresses multi computing kernel is obtained from the steering kernel using the formula,

$$k = SK + sF \otimes SK$$

Where,

k= noise suppresses multi computing kernel, SK = Steering kernel,
s = degree of sharpening, F = Laplacian filtering and $\otimes$ = convolution operator.

Smoothening matrix selection

The performance of the estimator depend on the choice of the smoothing matrix it extends the support (or footprint) of the regression kernel to contain “enough” samples. [13] It is reasonable to use smaller kernels in the areas with more available samples,whereas larger kernels are more suitable for the more sparsely sampled areas of the image.

EXPERIMENTAL RESULTS AND VALIDATION

Experiments on image denoising and deblurring are carried out to verify the effectiveness of the proposed method. In this section, we apply the proposed Switched Median Filter to image denoising task and NSSK method for image deblurring. For denoising and deblurring, the image is taken for preprocessing and then we perform pixel wise value estimation using Switched median filter and Steering Kernel estimation. Then we compare the performance of proposed method with several state-of-the art denoising methods. A simulation experiment is carried out using standard test images. We generate a noisy image by adding impulse noise range form 0.1 to 0.9 , noisy PSNR and denoised PSNR values are clearly stated in each iteration for the methods with Gaussian blur level of lambda =3 and sigma = 11 for Boat, Statue and Leana Image for testing. Then we perform denoising using fuzzy denoising and different methods. The results are summarized in the table with its PSNR values adopted as an evaluation metric for denoising result. The fuzzy switched steering kernel [13] is also used for objective evaluation. From the Table-1, the proposed Switched Median Filter performs better than fuzzy denoising, Steering Kernel Regression, Wainer filter and different denoising methods. Finally the computational time is far better than previous denoising methods. The time complexity table and time is shown for the noise variance for 0.1 to 0.5 and compared with Wainer filter, fuzzy filter and the proposed method. Even though when Wainer filter is applied it takes less time with the proposed method but the visual quality doesn’t have good appearance. This clearly verifies the effectiveness of exploiting both impulse and Gaussian blur in the proposed method. The performance of the proposed method is also better than fuzzy switched steering kernel with some limitations on edge deviation shown in Figure-6(f).[13], which is learning based denoising method and requires additional training phase before denoising.

Table-1. Comparison of PSNR values for images at different noise densities for the proposed method.

Proposed method						
Comparison, Gaussian blur level (lambda=3,sigma=11)						
Noise range	Boat image		Statue image		Leana image	
	Noisy PSNR	Denoised PSNR	Noisy PSNR	Denoised PSNR	Noisy PSNR	Denoised PSNR
0.1	16.36837086	25.22536116	17.28757379	32.48085783	16.94497259	30.42337821
0.2	13.89504995	24.99665143	14.72601868	32.00536785	14.23272925	30.40927071
0.3	12.52893079	24.77190355	13.18191852	31.86540103	12.68889565	30.39351806
0.4	11.31583883	24.67908078	12.07325332	31.43954192	11.40626919	30.16390105
0.5	10.40244503	24.4660034	11.07714549	31.12314094	10.50336589	30.09410934
0.6	9.650114736	23.95750222	10.32291688	30.63640932	9.77799102	29.69060962
0.7	9.00925181	23.52840436	9.672787763	30.12917582	9.162817891	29.25795149
0.8	8.457805307	23.35067794	9.165672478	30.26819096	8.570799852	29.08750359
0.9	7.992545469	23.05180983	8.614429598	29.11642852	8.079896312	28.63086534

Table-2. Comparison of PSNR values for images at different noise densities using fuzzy steering kernel.

Fuzzy Steering Kernel (NSSK) filter						
Comparison, Gaussian blur level (lambda=3,sigma=11)						
Noise range	Boat image		Statue image		Leana image	
	Noisy PSNR	Denoised PSNR	Noisy PSNR	Denoised PSNR	Noisy PSNR	Denoised PSNR
0.1	16.36837086	24.02536	17.28757379	29.95116	16.94497259	29.45308
0.2	13.89504995	23.65665	14.72601868	28.72938	14.23272925	28.68526
0.3	12.52893079	23.2919	13.18191852	27.61914	12.68889565	27.63978
0.4	11.31583883	23.05908	12.07325332	26.23227	11.40626919	26.37117
0.5	10.40244503	22.706	11.07714549	22.83181	10.50336589	22.88544
0.6	9.650114736	22.0575	10.32291688	21.97181	9.77799102	22.35521
0.7	9.00925181	21.4884	9.672787763	21.46595	9.162817891	21.92118
0.8	8.457805307	21.17068	9.165672478	21.52274	8.570799852	21.83295
0.9	7.992545469	20.73181	8.614429598	20.90087	8.079896312	21.34643

Table-3. Comparison of PSNR values for images at different noise densities and time per seconds.

Noise variance	**Wiener**(sec)	**Fuzzy steeringKernel**(sec)	**Proposed**(sec)
0.1	2.34	246.04	23.64
0.2	2.36	310.75	24.27
0.3	2.38	336.52	24.98
0.4	2.46	341.9	25.83
0.5	2.49	368.43	26.45

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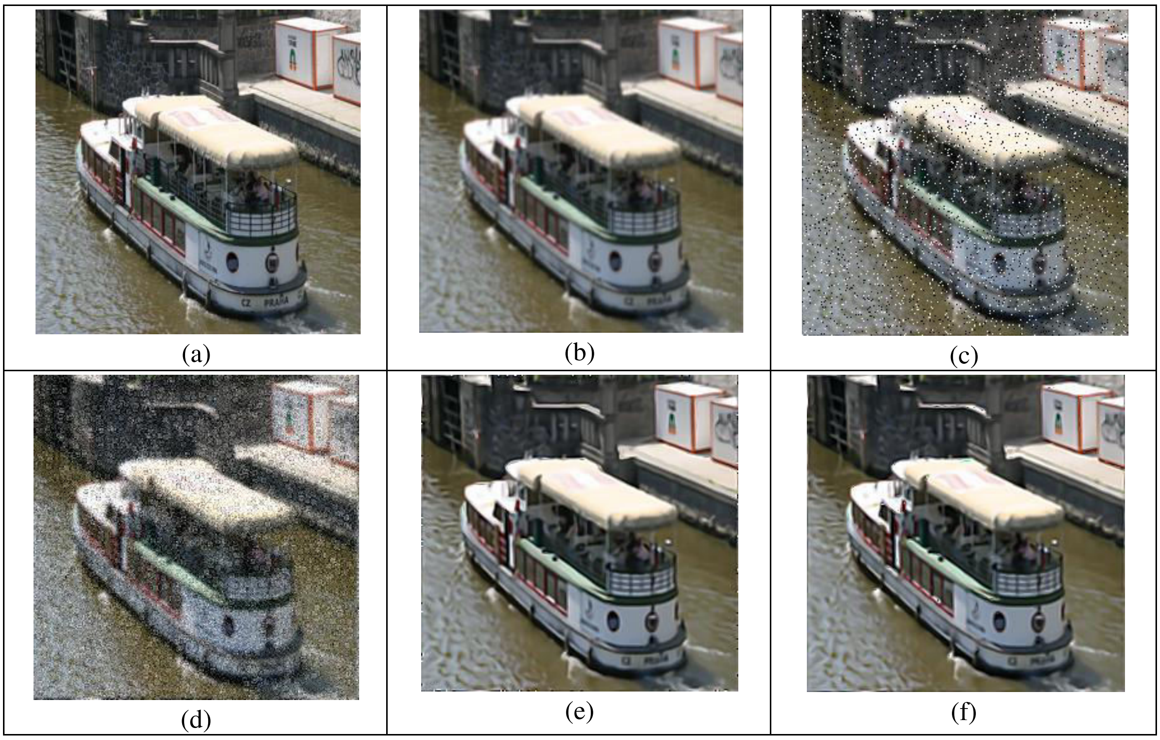

Figure-4. a) Original image b) Blurred image c) Noise with blurred d) Wiener filtered e) Fuzzy with steering Kernel(NSSK) f) Proposed method (Noise-0.1,lamda-3,Sigma-11).

Figure-5. a) Original image b) Blurred image c) Noise with blurred d) Wiener filtered e) Fuzzy with steering Kernelf) Proposed method (Noise-0.5,lamda-3,Sigma-11).

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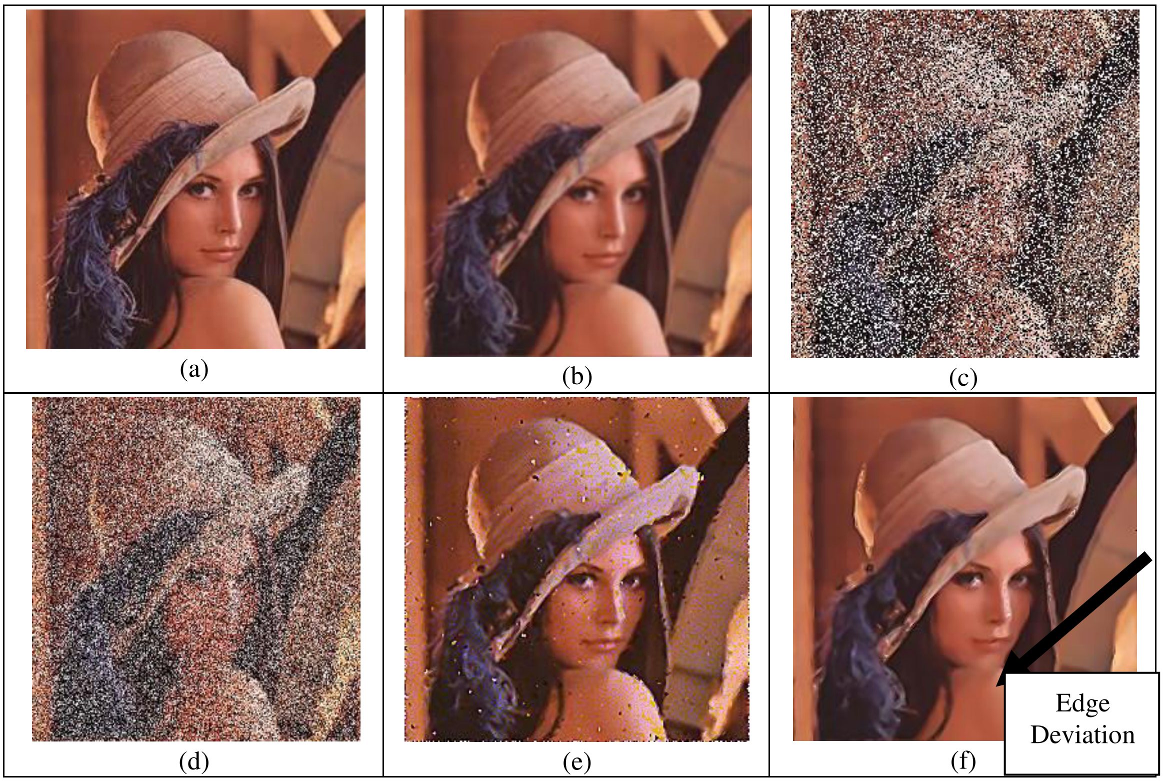

Figure-6. a) Original image b) Blurred image c) Noise with blurred d) Wiener filtered e) Fuzzy with steering Kernelf) Proposed method (Noise-0.9, lamda-3, Sigma-11).

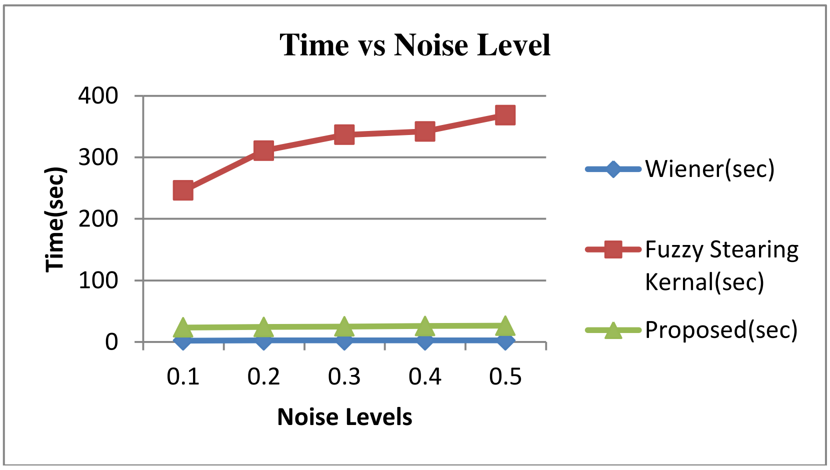

Figure-7. Time complexity diagram.

CONCLUSIONS

The recovery of the sharp image from unsymmetrical high density impulse noise and Gaussian blur is important for any image restoration applications. In this perspective we have identified and analyzed the potential and limitations latent in recent methods when handling high density impulse noise and Gaussian blur. Then we designed an image restoration based on switched median filter which replaced fuzzy techniques to over come this issue. Our future work will be focused on developing fast algorithm of the proposed method and applying the proposed method to other related applications. The limitations in the proposed method are when noise level is high there is some deviation in edge mapping that has been shown in the output. We have validated our work with experimental results that our proposed method is capable of performing denoising comparable to the state of the art methods as well as real noise.

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