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Color Image Restoration: A Technical Survey

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ABSTRACT

Abstract: Image restoration deems to reconstruct or recover a original image from degraded image by utilizing *a priori* knowledge of the degradation phenomenon which is also called as ill-posed inverse problem. In image restoration problem or ill-posed inverse problem, the information loss due to image acquisition and transmission is restored based on some constraints which are suitable for natural images and medical images. The main objective of this review paper is to propose fuzzy and optimization based restoration algorithm is more suitable for ill-posed inverse problems and to reduce Gaussian and Impulse noise while transmission and acquisition in natural color images and medical images. There are various methods that are available in the literature to handle ill-posed problems and noises that are occurred while transmission and acquisitions. . The conventional techniques called filter based techniques, statistical measure based techniques and optimization based techniques are available to handle both type of noise. All above methods are having their merits and demerits. In this survey, the restoration problem is considered as multiobejctive optimization problem. In existing methods, there is a need for optimization for improving the performance of the results. In this regard to avoid separate optimization, the restoration problem is considered as the multiobjective optimization problem. The comparative results shows optimization based restoration algorithm gives high PSNR, structural similarity values. It has the limitation of computational time.

KEYWORDS: Image Restoration, Statistical model, Filter based model, Optimization based restoration, Fuzzy, Optimization algorithm

INTRODUCTION

In this survey, the proposal for considering image restoration problem as a multi-objective problem, removing noises by optimization algorithm and uncertainty in noise identification is handled using fuzzy. By combining fuzzy and multi-objective optimization algorithm, the quality outputs are derived. The contribution of this literature survey is to propose the optimization based algorithms best for ill-posed inverse problems and reducing noise in the image as well it increase the quality of the image in terms of PSNR, FSIM. The main contributions are giving brief introduction about image restoration and the specific additive noise model description. The methods that are available in this literature to handle image restoration problems are classified based on statistical techniques, filtering techniques, optimization techniques, Gaussian noise reduction techniques, fuzzy techniques, fuzzy optimization techniques. The purpose of this study is to give knowledge about image restoration algorithms and their merits and merits and concluded that for handling real world problems, multi-objective optimization based algorithms are suitable for image restoration removing noise at the same time preserving fine details.

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Image Restoration is the process of recovering an image that has been degraded by a priori knowledge of degradation phenomenon. It is also defined as modeling a degradation process and applying the inverse process to recover the original image. The degradation modeling process can be modeled as in the following manner

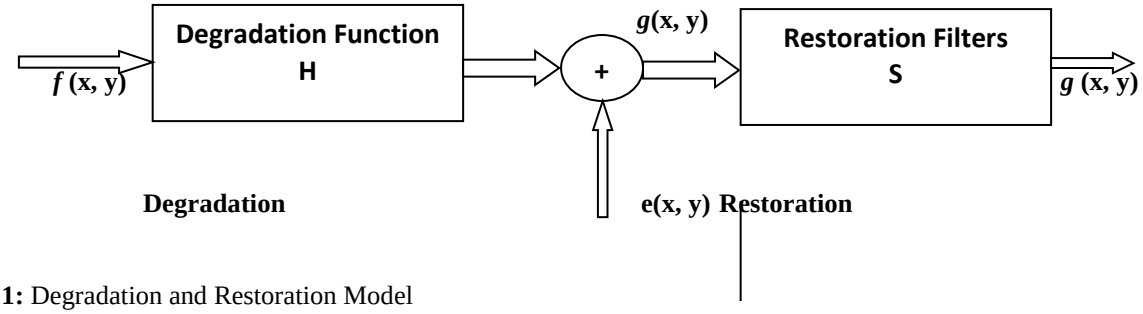

Fig. 1: Degradation and Restoration Model

Image restoration is modeled in spatial and frequency domain. If H is linear and position invariant then the representation for spatial and frequency domain representation are given in the equation (1) & (2). In spatial domain, the degradation model can be represented in the following form

$$g(x, y) = h(x, y) * f(x, y) + \eta(x, y) \quad (1)$$

In frequency domain, the degradation model is represented in the following format

$$G(u, v) = H(u, v)\, F(u, v) + \eta(u, v) \quad (2)$$

The principal source of noise in the image is occurred during acquisition and transmission process. While acquisition, the noise is incurred in the image due to light levels, camera motion, sensor temperature and the quality of sensor elements. In transmission process, the noise is occurred in the image due to poor environment condition due to light levels, atmospheric disturbances in wireless sensor networks. The Noise is having their own spatial and frequency properties. The spatial property of the noise is independent of the spatial coordinates; noise is uncorrelated with respect to image itself. The frequency domain property of the noise is frequency spectrum of noise distribution is zero. Noise is considered as the random variable of some probability distribution function. There are various probability distribution functions are used to represent the types of noises. In this survey, only additive noise is considered because additive noises are occurred when transmission and acquisition.

1.1 Gaussian Noise model:

It is also called as electronic noise because it arises in amplifiers or detectors. Gaussian noise caused by natural sources such as thermal vibration of atoms and discrete nature of radiation of objects. The Gaussian noise model is represented using the following probability distribution function is in Eq.(3) and image is shown in Fig.2.

Fig. 2: Gaussian Noise with Std Deviation 0.4

$$\mathbf{P(z)} = \frac{1}{\sqrt{2\pi\sigma}} e^{-(z-\mu)^2 / 2\sigma^2} \quad (3)$$

z – Gray level of the image
μ - Mean of the average of z
σ – Standard deviation of z

1.2 Impulse Noise Model:

The impulse noise model also called data drop noise because statistically its drop the original data values. This noise is also referred as salt and pepper noise. However the image is not fully corrupted by salt and pepper noise instead of some pixel values are changed in the image is shown in Fig.3. The probability distribution is shown in Eq.(4).

$$\mathbf{P(z)} = \begin{cases} \mathbf{P_a}, & \mathbf{for\ z=a} \\ \mathbf{P_b}, & \mathbf{for\ z=b} \\ \mathbf{0}\ , & \mathbf{otherwise} \end{cases} \tag{4}$$

If the $P_a \neq 0$ and $P_b \neq 0$ then the noise is bipolar, if $P_a = P_b = 0$ then the noise is unipolar.

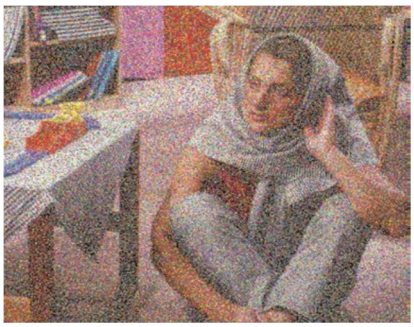

Fig. 3: Impulse Noise with density 30

In inverse problem, in order to minimize the error with prior information some regularization parameters are added to improve the quality of the image.

$$\tilde{x} = argmin(\|g - h * x\|^2) + \lambda * \Omega(x) \tag{5}$$

In equation (5), '$\tilde{x}$' is the estimated solution, '$g - h * x$' is the residual error and 'λ','$\Omega(x)$' are regularization parameter and smoothing function for setting the value of the regularization parameter. There are some criteria for setting values of regularization parameters to improve the quality as well to preserve the image fine details. By assigning more weight to regularization factors, the restoration leads to form artifacts in the result. If the minimal weights are assigned to regularization parameters, the restoration results are blurred [1], [2]. In order to avoid the problems related to regularization parameters in ill- posed inverse problems, the image restoration is treated as statistical based methods [3],[4],[5] filtering based methods [6], [7] and optimization based methods [8], [9].

Due to the nature of image formation medium and transmission medium, the common noise like Gaussian and impulse noise are included in the image. The conventional technique available for reducing the Gaussian noise is averaging or smoothing technique. The Gaussian noise identification techniques are based on the zero mean property of the noise pixel. Linear methods and nonlinear methods available in the literature are used to identify the Gaussian noise only [10], [11], [12]. The very basic linear method for Gaussian noise is the Gaussian filter. The common method used to remove impulse noise in the image is median filter. In both types of noise, the standard methods are for removing noises but or not for preserving the fine details in an image.

Usually the restoration performance depends on the process of identifying the noise pixels in image rather than wrongly predicting the fine details as a noise in an image. The restoration problem is considered as a two stage problem. In the first stage, noise identification and in the second stage noise reduction is carried out. There are a number of methods available in the literature to identify the type of noise and restore the noise including arithmetic mean filter, adaptive methods and soft switching methods [13], [14], [15], [16]. All the above methods remove noises but it does not predict the fine details in a precise manner. This leads to the use of fuzzy based technique. There are various fuzzy based methods available for identifying and restoring both impulse and Gaussian noise in the literature. Fuzzy directional derivative filter [17], the fuzzy bilateral filter [18], the fuzzy noise reduction method [19], and fuzzy-switching filter [20] are some of the frequently used fuzzy techniques. The above papers in the literature deals with the concept of designing fuzzy based filters for restoring different noise and not considering details as impulses, which leads to preserve the details but not to reduce impulses efficiently. It leads to the peer group concept to restore the noises.

The self similarity measure is available in the literature to restore both impulse and Gaussian noise. It is called as peer group concept. There are a number of peer group methods [21], [22] available in the literature to remove both impulse and Gaussian noise. The peer group method based on threshold decision for identifying the

noise results in a crisp value. It is not suitable for handling the similarity measure as a precise one. Due to the fact of considering similarity measure as imprecise, the conventional peer group method is not suitable for handling the uncertainty problems which leads to fuzzy peer group method [23].

Along with fuzzy, Genetic Algorithm (GA) is combined to form better solutions called as Fuzzy Genetic Algorithm [24]. In the simple cases, there is only one objective criterion for optimization, either maximization or minimization of objective variables. In many real-world decision making problems, there is a need for simultaneous optimization of multi-objectives parameters [25], [26]. A fuzzy fitness finding mechanism uses the above multiple similarity measures that guides the GA through the search space to find optimum solution using genetic operators, crossover and mutation. The fuzzy rule based system is combined with the GA to form better solution in restoration. The optimization of multi-objective problem is considered as fuzzy rules in the GA. The traditional system has several limitations over GA. GA solves the problem of changing the fuzzy rule parameter values, obtaining the maximum value for the stopping criteria in an optimized manner. In image restoration problem, the multi-objectives are reducing noise in the image and at the same time preserving the fine details [27], [28], [29].

The deblurring of image is considered as inverse problem. It becomes ill-posed when noise contaminates the blurry image. The problem is very sensitive to small perturbation in data. Conventionally, smoothness constraints are considered as a remedy to cater the sensitivity of the problem.The fuzzy rule based regularization parameter estimation is proposed with quadratic functional smoothness constraint. For deblurring image in the presence of noise, a constrained least square error function is minimized by the steepest descent algorithm [61].

A regularization blind image restoration method using particle swarm optimization [62] was proposed in the literature. Regularization technique was adopted to solve ill-posed problem in the process of blind image restoration, the selection of regularization parameter still remains a difficult problem due to the amplification of noise in the inversion process. So two kind of particle swarm optimization were used to estimate regularization parameter and point spread function alternately.

A new iterative regularization procedure for inverse problems based on the use of Bregman distances, with particular focus on problems arising in image processing [63] is proposed. The main motivation is the problem of restoring noisy and blurry images via variational methods by using total variation regularization. The rigorous convergence results and effective stopping criteria for the general procedure is obtained using iterative regularization procedure by total variation optimization algorithm.

Literature Survey:

2.1 Statistical based methods:

The statistical wavelet models [30] are proposed for image restoration problems. When compared to spatial domain methods and frequency domain methods for image restoration, the image restoration problem is considered as wavelet domain methods based on statistical measures. In wavelet based image restoration, there are two advantages. The first advantage is that due to signal energy compaction nature in wavelet domain, there is a perfect separation of noise and original signal compared to spatial domain methods. The second advantage is that due to signal singularities in wavelet domain, the higher prediction of edge information and reducing the ringing artifacts in the restored image. The model parameters are estimated to restore the problems in orthonormal and translation invariant wavelet domains. The limitation of the work is the degradation model is assumed to be stationary to reduce the estimated risk in restoration problem.

The Joint Statistical model [31] for image restoration is proposed to achieve local smoothness and non local self similarity in natural images. There are three advantages in the joint statistical modeling approach. It is used to derive robust and reliable solution for image restoration with local smoothness and non local self similarity property. The joint statistical modeling is used to provide the solution for inverse problems. The joint statistical model is used to make the solution tractable and tracable along with therotical proof of convergence, Split Bregmen algorithm is developed to solve inverse problems efficiently. In order to achieve the specified local and nonlocal properties of an image, the better initialization is obvious. The images are tested with specific scale and orientation and limited performance on the mixed Gaussian and impulse noise.

The unsupervised information theoretic adaptive filter [32] is proposed for restoring the noise in the image based on improving the predictability between the image neighborhoods by the way of decreasing joint entropy. The proposed algorithm works with feature space metric leads to preserve rotational symmetry and allows for boundary conditions. The proposed methods leads to make image neighborhoods statistics are regular for achieving reliable image denoising.

A new statistics based method [33] is implemented for image restoration from poisson data using Gibbs prior. The proposed method is used to select the Gibbs parameters for Maximum a Posteriori Approach (MAP) image restoration from poisson data. In this method, a simple iterative feedback based algorithm is used to select the parameter for MAP image restoration. The method works with the assumption of the approximate value of the blurring function is known earlier. It takes only minimal number of iteration for parameter selection. The

blur varies widely from the true blur then there is a indication of better approximation of the blur should be specified.

The maximum entropy based image restoration [34] is used for astronomical images. The main objective of this method is to maximize the entropy of the noise image with the given image by applying the Bayesian probability theorem. It works well with the positivity and map images having point sources.

The frequency domain image restoration scheme [35] is proposed based on non iterative maximum entropy image restoration method for reducing circular blur in the images. The proposed method is used to reduce the computational complexity compared with the regular maximum entropy based restoration technique. The proposed work has the limitation of miserable performance for high resolution restoration of decimated and randomly sampled blurred versions.

2.2 Filter based Image Restoration:

A new fuzzy filter based on histogram computation [36] of the image input statistics is proposed. From the image histogram, the set of fuzzy if then rules are formed to design the filters for restoring high density impulse noise in the image. The proposed adaptive filter does not need any prior information about the image data. The proposed method is used to predict the image edge sharpness even when the high density noise is present in the image. The histogram based adaptive filter is simple and works well without having any prior knowledge about the image data. There is no need of training of input data compared with some other algorithms using neural network concept. The optimization technique is incorporated with the fuzzy adaptive technique in order to improve the non linear filter performance.

A new classifier-augumented wiener filter [37] for removing impulse noise is proposed in the image without including the operating pixel in the sliding window. It is used to exclude the center pixel from the sliding window if it is not affected by the impulse noise by the way of implementing the fuzzy classifier. In the augumented fuzzy classifier, the inclusion of fuzzy KNN scheme to detect the center pixel is affected by the noise or not. The proposed method works well for the real time noise and artificial impulse noise situation.

A new method based on Wiener filter [38] and edge map technique for restoring noise in the image is proposed. By varying the weights of wiener filter, the highly noise reduced image is generated. The edge map is constructed for noisy image. Using edge map and wiener filter, the noise affected image is restored with the edge preserving and fine details structure preserving capabilities. The proposed method works well for the different range of noise levels. The proposed method works faster compared with other algorithms and it is suitable for image having fine details and edges.

An effective filter for reducing the impulse noise based on switching median filter with boundary discriminative noise detection scheme [39] is proposed. The proposed method is very powerful to detect the pixel is corrupted by impulse or not. If the pixel is corrupted, then the variable window median filter is used to attenuate impulse noise in the image. The proposed method is used to identify the noise in the image pixel in very short time compared to ordinary boundary discriminative noise detection scheme.

A new histogram based fuzzy filter [40] for restoring high density impulse noise in the image is proposed. The fuzzy smoothing filter is designed with the fuzzy membership function in which the initial parameters are derived from the input histogram. The histogram computation is used to reduce the discrepancy between the reference intensity and defuzzification process. There is no prior knowledge is needed to identify the initial parameter setting. In the existing methods, there is a lengthy training is needed. The proposed method is suited for high density impulse noise and it is simple process to restore the noise with edge and fine detail preservation. The proposed method is not well suited for the other type of noise.

A new fuzzy filter [41] for reducing additive noise in the image is proposed. There are two stages in the filtering process. The fuzzy derivative is computed in eight directions of the image subwindow. Based on the fuzzy derivative, fuzzy smoothing operation is carried out based on weighting the contribution of neighboring pixel values. The process is applied in iterative manner along with statistical computation to preserve the homogeneity in the image based on noise distribution.

A new algorithm for reducing any kind of impulse noise restoration technique called fuzzy impulse noise detection and reduction method [42] is proposed. Using fuzzy gradient values for the noisy image, fuzzy set is formed. Based on the fuzzy set, the filtering process is carried out. In filtering process, the membership value from fuzzy set is used to implement the fuzzy averaging filter. The proposed method does not outperform the median based filter for random impulse noise but the detection method is used to provide the idea about the identification of impulse noise. The proposed method works for locally instead of globally to better elimination of random impulse noise in the image. The fuzzy detection and reduction method is not better for color image restoration.

A new noise adaptive fuzzy switching median filter for salt and pepper noise detection and removal [43] is proposed. The fuzzy histogram is used to identify the pixel is corrupted by impulse noise or not. The noise free pixels are not disturbed or unchanged while implementing noise restoration process. The noise adaptive fuzzy

switching median filter employs fuzzy reasoning mechanism to handle the uncertainty problems extracted as the local information introduced by the noise in the filtering process.

2.3 Optimization based restoration:

Genetic algorithm with laplacian constraint for gray image restoration [44] is proposed. The restoration problem is considered as a optimization problem whose cost function is minimized by the way in which the genetic algorithm parameters are modified. The cost function is designed by combining appropriate prior constraint as laplacian constraint for selecting population of chromosome to form the proper solution for the ill posed inverse problems. The computational cost is reduced by implementing the parallel work of GA. The future study in this work is to consider the higher size image is to be processed by the way of reducing computational complexity.

Optimization based image restoration [45] is best suited for the degraded image contain more edges and convert the ill posed problems into well posed problems. The assumption for the proposed work is the noise is gaussian and has a zero mean. In this method, the regularization parameter controls the trade off between good fit to the data and regularity of the solution. Active set for solving bounded value regularized image restoration problems. The SAC method for semi adaptive and strictly convex formulation is proposed that better preserve smooth surfaces. The proposed method does not fully capture the overall quality of the reconstructed image. The proposed work does not work for color images.

An evolutionary based image restoration [46] for space variant degradation problems is proposed. Pseudo convolution is an effective approach for restoring space variant degradation problems. The restoration is formed as the minimization of constraint least square error. The proposed method implements genetic algorithm and particle swarm optimization as two evolutionary algorithms to obtain optimum solution for restoration with adaptive regularization. Increasing the image size introduces a new problem by expanding the search space exponentially. Thus, a hybrid meta-heuristic solution is further proposed for enhanced diversity for global convergence. For space invariant degradations, restoration improvements and computational complexities are dependent on the size of the image. In future, different size of image is to be analyzed.

The Genetic algorithm (GA) based image restoration [47] with isophote constraint is proposed. The image restoration problem is modeled as an optimization problem in which the problem is solved by a cost function with isophote constraint that is minimized using a GA. In the proposed work, the Caption in TV advertisements and frames are removed using GA based approach. estimate the value of smoothness, given by the best chromosomes of the GA and project this value in the

isophotes direction. This method restores the inside of the region using the geometric features of the image from the surrounding area. The future work of the proposed work is to implement the caption detection with non static background and for video sequence.

Color image denoising method for multichannel data set image restoration [48] is proposed. The main issue in image restoration filters is how to select best filter parameter that weights the inputs to the filters. The author proposes an evolutionary computation based approach to select and optimize the coefficients in the class of weighted vector directional filters. Using a genetic algorithm is able to predict the filter weights to match varying image and noise characteristics. The proposed GA optimization concept significantly improves color/structural preserving characteristics of the traditional color filtering schemes, while exhibiting acceptable noise attenuation capabilities.

A new algorithm based on majorization and minimization [49] and wavelet for image restoration is proposed. The main issue in wavelet based image resoration is the non-Gaussian (heavy-tailed) wavelet priors lead to objective functions which are nonquadratic, usually nondifferentiable, and sometimes even nonconvex. The problems are solved by majorization and minimization algorithm for wavelet image priors. The proposed method handles the famous issue of singularity issue related to infinite weight scheme. The proposed work handle low level blur and mild to large noise. The weak blur and middle to high noise situations to be handled in future.

Genetic algorithms [60] are customized to accommodate multi-objective problems by using specialized fitness functions and introducing methods to promote solution diversity. Optimizing a particular solution with respect to a single objective can result in unacceptable results with respect to the other objectives. A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution.

2.4 Gaussian noise restoration methods:

A Gaussian kernel based filter [50] for restoring Gaussian noise in the image is proposed. In this method, the noise is zero in harmonic parts of the image and very large values in the edge and texture part of the image. It is the basic model filter for removing Gaussian noise in the image. It is very simple. As a consequence, the Gaussian based convolution is optimal in flat parts and edges and texture parts are blurred.

An anisotropic diffusion method [11] is proposed for restoring Gaussian noise in the image with scale space and edge preservation properties. The coarse resolution images are generated by the convolving the gaussian kernel with the image. in coarse resolution images, the semantic edge locations are not predicted well. To avoid the problem, scale space restoration algorithms are introduced. In this method, no new maxima are generated to preserve the local boundaries with sharp regional properties. The global way of noise estimation does not provide an accurate local estimation and the local estimation of gradients provides too partial piece of information for distinguishing noise related areas and edges. The problem is avoided by introducing local estimation noise in the anisotropic diffusion process.

A total variation minimization method [51] is proposed for restoring noise in the image by considering the problem as a minimization problem. The lagrange multiplier is introduced in minimization problem. At each step of minimization problem, the difference between the noisy image and the recovered original image is minimized. The lagrange multiplier value is fixed based on the statistics of the noise and the degree of the filtering. The limitation of this work is more detail knowledge about the noise and the original image is needed to get more detail of the solution.

A bilateral filter [12] is described for reducing Gaussian noise based on neighborhood pixel concept. In this method, instead of considering fixed spatial image neighborhood it also weighting the distance to the reference pixel. The neighborhood algorithm in bilateral filter does not blur the edges in the image. The problem with this method is that comparing only grey values of the neighboring pixels when this pixels are noisy. The image neighborhood filters are also creates artificial shock.

A non local means algorithm [52] is proposed for image denoising. The non local means algorithm is used to reduce the noise by applying non local averaging pixels in the image neighborhoods. The non-local means algorithm does not make any assumptions about noisy and original image. The non local means algorithm assumes that the image contains an extensive amount of redundancy as a noise. The proposed method does not provide any guarantee to higher visual quality of restored image.

The probabilistic non local image [53] is proposed denoising algorithm for restoring noise in the image. The main objectives of the proposed algorithm are overcoming the defects of weight function used in classical non local means algorithm. The proposed algorithm provides therotical statistics of patch-wise difference for Gaussian noise to efficiently identify the noisy pixel in the patches. Along with that the probabilistic non local means algorithm use prior information to formulate probabilistic weight difference reflecting true similarities between the two noisy pixels.

The principal neighborhood dictionaries [54] are proposed for non local image denoising. The non local image denoising algorithm uses principal component analysis to achieve high accuracy while reducing computational loads. Image neighborhood vectors are projected onto the lower dimensional subspace using principal component analysis. The subspace selection is done using parallel analysis. The non local image denoising scheme is implemented in the projected subspace also reducing the computational load by parallel computing the subspace. The limitation of the proposed is the color image restoration not achieved with the single step. There is a separate restoration for the three channels.

The principal component analysis and local pixel grouping mechanism [55] is proposed for denoising Gaussian noise in the image. The edge preserving and structure preserving capapbilties are obtained by modeling image pixels and its neighbors as vector variables whose training samples are selected using local pixel grouping concept. The image local feature is preserved after coefficient shrinkage in the principal component analysis domain to remove noise. The training sample selection procedure is necessary for optimally selecting the sample blocks.

2.5 Color Image Restoration:

A fuzzy peer group based method [23] is proposed for mixed Gaussian and impulse noise removal. The fuzzy peer group is formed based on the novel fuzzy logic procedure. The peer group window concept for identifying noise in the image sub window is combined with the fuzzy concept to predict the uncertainty in the image pixel to compute whether the pixel is corrupted by noise or not. The Fuzzy rule based switching impulse noise filter is used to restore the noise in the fuzzy peer group window. In peer group formation, the customized fuzzy membership is introduced to proper identification noisy pixel in the peer group window. The impulse and gaussian noise are restored using fuzzy peer group averaging and vector median filter respectively.

The peer group filtering [56] and color image quantization technique for impulse noise restoration is proposed. The image pixels are replaced by weighted average of neighborhood similarity of the peer group window. Local statistics are obtained after peer group filters acts as weights are applied to quantize the color clusters in the region. The peer group filter is used to restore the impulse noise in the color image as well predict edges and the peer group filter is used in color image quantization application.

A new fuzzy filter [42] is proposed for the reduction of additive noise present in the image. There are two steps in the proposed filter. The first sub filter computes fuzzy distances between the color components of the central pixel and its neighborhood. These distances determine in what degree each component should be

corrected. The goal of the second sub filter is to correct the pixels where the color components differences are corrupted. The main advantages of the proposed filter are simple for the denoising capability and the reconstruction capability of the destroyed color component differences.

The proposed work has the limitation of applying other fuzzy filters and for other types of noises like speckle noise and stripping noise.

A new two fuzzy filters [57] is proposed for removing of both impulse and Gaussian noise. The first sub filter detects the noisy pixel along with the amount of noise in it by utilizing three fuzzy membership functions. The corrupted pixels are then corrected using the median of the noise free pixels. The second sub filter makes use of the relation between different color components of a pixel to remove the residual noise in the color image. For the removal of the Gaussian noise, an adaptive distance between color component pairs of the central pixel and the neighbourhood pixel to determine the weight of the latter. The weighted average of the weights of all the neighbourhood pixels helps compute the correction term for the Gaussian filter. A cascade combination of the two fuzzy filters in which the output of the Impulse filter is fed to the input of the Gaussian filter is shown to effectively eliminate the mixture of Gaussian and Impulse noises from color images.

2.6 Fuzzy optimization based restoration algorithms:

The Impulse Noise Removal from Medical Images Using Fuzzy Genetic Algorithm (FGA) [24] is proposed. A proposed technique uses Fuzzy Genetic Algorithm to find the optimal composite filters for removing all types of impulse noise from medical images. A Fuzzy Rule Base is used to adaptively change the crossover probability of the Genetic Algorithm used to determine the optimal composite filters. FGA is used to determine the optimal composite filters for removing different levels of impulse noise from medical images without using deep knowledge about noise factors The proposed technique is used for noises in the satellite images.

An adaptive genetic operators based on co evaluation with fuzzy behaviors [25] is proposed. The proposed works presents a technique for adapting control parameter settings associated with genetic operators. The goal is to obtain fuzzy rule bases that produce suitable control parameter values for allowing the genetic operator to show an adequate performance on the particular problem to be solved. The use of fuzzy logic based techniques for improving the behavior of Genetic algorithm. The application of GA along with fuzzy is applicable for search and optimization problems.

Genetic Fuzzy Systems -Evolutionary Tuning and Learning of Fuzzy Knowledge Bases [26] is proposed. A fuzzy evolutionary algorithm is an EA that uses Fuzzy Logic techniques to adapt its parameters or operators to improve its performance. The objective of this self adaptation is to adjust the GA optimization process itself to the fitness landscape of the underlying problem. A GA expert formulates fuzzy control rules to adapt the GA parameters, which achieve an optimal balance between exploitation and exploration through the GA execution.

The fuzzy filter based on particle swarm optimization [61] is used to remove the high density image impulse noise. The merging of the particle swarm optimization with the fuzzy filter helps to build an auto tuning mechanism for the fuzzy filter without any prior knowledge regarding the noise and the true image.

Comparative Analysis:

In the comparative analysis, some of the standard methods and fuzzy based methods for removing impulse noise are considered. The fuzzy based methods are Symmetrical Triangular fuzzy filter with Average center (TMAV), Asymmetrical Triangular with Moving Average center (ATMAV) [58, 59], Symmetrical Triangular fuzzy filter with Median center (TMED) [58], [59] Asymmetrical Triangular fuzzy filter with Median center (ATMED) [58], [59] methods results are taken. In all above methods, the averaging scheme or median based calculation was used to smooth the noise. It leads to loss of fine details and the edges were not preserved. Noise Adaptive Fuzzy Switching Median Filter (NAFSM) [43] method results are taken. In NAFSM, the efficient utilization of processing time depends on the density of the noise. The performance of the NAFSM method is reduced while processing high density of noise in an image due to trade -off between the filtering complexity and the processing time. The results of Gaussian noise affected image using the existing methods like Non Local Means (NLM) [52], Probabilistic Non Local Means (PNLM) [53], are considered as standard methods and their corresponding results were taken for comparison. All above methods for Gaussian noise restoration are related to the neighborhood similarity that leads to the limitation of performance, in terms of fixing the search window size and processing time. In wavelet based method, the problem is related to finding the true wavelet coefficient to get the optimum result visually and numerically. The Principal Neighborhood Dictionary (PND) [54] method takes long time to produce optimum results in terms of visual quality due to implement PND for three color components of RGB image separately and the complexity is also related to identifying the principal component. The Principal Component Analysis (PCA) [55] based method results are compared. Along with various optimization based restoration algorithms results are also compared. The following optimization algorithms for image restoration like Steepest Descent [61], PSO [62], TV minimization [63], Ant colony based optimization [64] results are considered for comparison. The comparative analysis in terms of PSNR, MSE,

FSIM and NCD is given in the Table 1. The comparative study represents high density impulse noise restoration methods and high standard deviation Gaussian noise restoration methods and methods for restoring both noises.

Table 1: PSNR, MSE, FSIM and NCD Comparison for High Density (70%) Impulse Noise and Gaussian Noise with standard deviation(Above 5) Existing Restoration Methods.

Methods	Computational Time (s)	PSNR	MSE	FSIM	NCD
Impulse Noise restoration Methods					
MAP	500	25.41	441.23	0.43	53
Maximum Entropy	470	26.71	438.14	0.43	43
Information Theoretic	475	26.23	451.25	0.42	45
Joint Statistical	485	27.17	468.23	0.51	38
Wavelet	380	30.23	341.56	0.7	23
ATMAV	300	35.67	300.12	0.76	21
ATMED	275	34.23	299.13	0.8	19
TMAV	225	36.76	321.77	0.6	28
TMED	190	33.26	320.18	0.73	24
FRINRM	155	39.47	249.12	0.7	17
Gaussian Noise Restoration Methods					
PND	180	38.45	267.37	0.7	18
PNLM	185	38.01	263.67	0.6	20
PCA	190	37.38	243.78	0.7	18
Gaussian and Impulse noise (Mixed) Restoration Methods					
NAFSM	180	37.56	318.21	0.78	18
FPG	140	40.45	248.23	0.8	14
Total Variation Minimization	230	41.06	231.89	0.7	16
Ant colony	360	40.67	251.76	0.6	13
Fuzzy +Genetic	320	41.16	220.13	0.7	11
Fuzzy +PSO	315	42.45	200.43	0.7	10

Conclusion and Future Enhancement:

In Statistical Based Restoration, the noise identification and density computation task is easy because of statistical properties of noise in the image. The flow of computation is based on assumption related to probability measure makes the problem more clear and easy computation. It is applicable for both spatial domain and frequency domain image models. More number of parameters are needed. There is a Proper assumption related to noise model. The regularization parameter needed to achieve reliable solution. There is a trade-off between noise and smoothing parameters in the restoration model. In Filter Based Methods, it is easy for implementation by the way of convolution process. Noise is filtered out easily by the local processing. Adaptive schemes are available in the literature for handling edges and the texture in the images. Image Boundaries are predicted well by the combination of statistical feature along with restoration scheme. The image quality is limited to density of noise even if there is adaptive procedure accompanied with filtering process. There is a problem related to fixing the sliding window size of the convolution mask. There is another problem related number of time the filter is applied to degraded image. There is a separate scheme is combined to predict the prompt size for sliding window. There is a separation of image texture part and noise part separately before applying the restoration algorithms. In optimization based methods, the optimum solution is obtained either by minimizing and maximizing the constraints offered by the techniques. The very basic problem in optimization based technique is number of iteration to achieve optimum solution and the computational time. In order to predict the uncertainty in the degraded image, the fuzzy concept is very useful to identify the noise affected pixel alone not disturbing regular pixel in the image. Along with fuzzy, GA is combined to form better solutions called as Fuzzy Genetic Algorithm. In the existing fuzzy genetic algorithm, the genetic algorithm is used for

only choosing the best filter from the set of filters for noise restoration, choosing optimum value for the filter parameter, choosing best sub window size for noise restoration by convolution.

In this survey, the image noise restoration problem or ill-posed inverse problem is considered optimization problem by implementing the optimization parameters on the image noise pixels directly. In the simple cases, there is only one objective criterion for optimization, either maximization or minimization of objective variables. In many real-world decision making problems, there is a need for simultaneous optimization of multi-objectives parameters. A fuzzy fitness finding mechanism uses multiple rules in the problem domain that guides the optimization algorithm through the search space to find optimum solution using optimization operations. The traditional system has several limitations over fuzzy optimization. The optimization algorithm solves the problem of changing the fuzzy rule parameter values, obtaining the maximum value for the stopping criteria in an optimized manner. From this survey, multi-objective fuzzy optimization algorithm approach is better for handling ill-posed inverse problems in restoring both impulse and Gaussian noise in the color image and improving quality as well. The limitation is considered for fuzzy optimization based image restoration algorithm is computational time.

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