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IMAGE DENOISING TECHNIQUES: LITERATURE REVIEW

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***Abstract*-In various fields and applications use of images are becoming increasingly popular like in field of medical, education etc. But the problem is that noise will be inevitably introduced in the image during image acquisition process. Another problem that arises after denoising process is the destruction of the image edge structures and introduction of artifacts. For this there are several techniques proposed by other authors for image denoising as well as for edge preservation. In this paper, we aim to provide a review of some of those techniques that can be used in image processing (denoising). This paper outlines the brief description of noise, types of noise, image denoising and then the review of different techniques and their approaches to remove that noise. The aim of this review paper is to provide some brief and useful knowledge of denoising techniques for applications using images to provide an ease of selecting the optimal technique according to their needs.**

Keywords—Image Denoising; Salt-and-pepper noise; Gaussian noise; Gaussian distribution; MSE; PSNR; Thresholding

I. INTRODUCTION

Any form of signal processing having image as an input and output (or a set of characteristics or parameters of image) is called image processing. In image processing we work in two domains i.e., spatial domain and frequency domain. Spatial domain refers to the image plane itself, and image processing method in this category are based on direct manipulation of pixels in an image [2] and coming to frequency domain it is the analysis of mathematical functions or signals with respect to frequency rather than time.

The principal sources of noise in digital images arise during image acquisition and/or transmission [2]. It can be produced by the sensor and circuitry of a digital camera or scanner. Noise degrades the image quality for which there is a need to denoise the image to restore the quality of image. Hence, first the question arises is what is noise?

Definition: Image noise means unwanted signal. It is random variation of color information and brightness in images, and is usually an aspect of electronic noise. It is an undesirable by-product of image capture that adds spurious and extraneous information.

This definition includes everything about a noise. Many applications are now including the images in their procedures, methods, reports, manuals, data etc., to deal with their clients and image noise is the basic problem with these applications as it affects the data accuracy and efficiency level.

The rest of this paper is organized as follows. Section 2 outlines the image denoising including types of noise and some noise filtering techniques. Then, Sections 3rd and 4th discuss, in brief the need for edge preservation and detection and literature review of the denoising techniques in each domain. The last section consists of the conclusion.

II. IMAGE DENOISING

A. Types of Noise

- *Gaussian noise* – One of the most occurring noise is Gaussian noise.Principal sources of Gaussian noise arise during acquisition e.g. sensor noise caused by poor illumination and/or high temperature, and/or transmission e.g. electronic circuit noise. Gaussian noise represents statistical noise having probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution.In other words, the values that the noise can take on are Gaussian-distributed.

  The probability density function p of a Gaussian random variable z is given by:

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

where z represents the grey level, μ the mean value and σ the standard deviation [1]. The standard model of this noise is additive, independent at each pixel and independent of the signal intensity, caused primarily by thermal noise. The mean of each distributed elements or pixels of an image that isaffected by Gaussian noise is zero. It means that Gaussian noiseequally affects each and every pixel of an image.

- *Salt-and-pepper noise*–Fat-tail distributed or "impulsive" noise is sometimes called salt-and-pepper noise.Any image having salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. In salt-and-pepper noise corresponding value for black pixels is 0 and for white pixels the corresponding value is 1. Hence the image affected by this noise either have extreme low value or have extreme high value for pixels i.e., 0 or 1.Given the probability r (with 0<= r<=1) that a pixel is corrupted, we can introduce salt-and-pepper noise in an image by setting a fraction of r/2 randomly selected .pixels to black, and another fraction of r/2 randomly selected pixels to white. This type of noise can be caused by analog-to-digital converter errors, bit errors in transmission, etc. Elimination of salt-and-pepper noise can be done by using dark frame subtraction and interpolating around dark/bright pixels.

- *Shot noise*– In the lighter parts of an image there is a dominant noise from an image sensor which is typically caused by statistical quantum fluctuations, that is, variation in the number of photons sensed at a given exposure level called photon shot noise. Shot noise follows a Poisson distribution, which is somehow similar to Gaussian.

- *Quantization noise(uniform noise)* – This noise follows an approximately uniform distribution and also known as uniform noise. Quantization means the process of dividing, hence the noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise. Though it can be signal dependent, but if dithering is explicitly applied it will be signal independent.

- *Anisotropic noise*–Some noise sources show up with a significant orientation in images. For example, image sensors are sometimes subject to row noise or column noise [1].

B. Noise Filtering Techniques

- *Removing Noise by Linear Filtering*– Linear filtering is use to remove certain types of noise. Averaging or Gaussian filters, are appropriate for this purpose. For example, an averaging filter can remove noise or grain from a photograph by replacing each pixel value with the average value of its neighbourhood pixels. By this local variations caused by grain are reduced.

- *Removing Noise by Median Filtering*– Median filter is a non-linear filter which is similar to an averaging filter. In this the value of an output pixel is determined by replacing the value of each corresponding pixel by the median of the neighborhood pixels, rather than the mean. The median is much less sensitive than the mean to outliers (extreme values). Median filtering is therefore better to remove outliers without reducing the image sharpness.

- *Removing Noise by Adaptive Filtering*– A Wiener filter (a type of linear filter) is applied using wiener2 function to an image adaptively, tailoring itself to the local image variance. Whenever there is large variance , wiener2 performs little smoothing and vice versa. This approach produces better results than linear filtering. The adaptive filter is more selective than a comparable linear filter, as it preserves the edges and other high-frequency parts of an image. In addition, there are no design tasks; the wiener2 function handles all preliminary computations and implements the filter for an input image. wiener2, however, does require more computation time than linear filtering.

III. EDGE DETECTION

As we have many techniques and filters to remove noise (some of them are discussed above) there is a problem of loss of edge information. After denoising edge information will be lost hence we need to preserve edge information and at the same time preserve the edges. Edge features are an important component of image under study because they represent the major characteristics of the image objects and are easier to capture our visual attention. Therefore, edges should be well preserved during image denoising.

The most common and widely used approach for edge detection is canny edge detection. Algorithm for canny edge detection runs in five steps:

1. *Smoothing*: Blurring of the image to remove noise using filter.

2. *Finding gradients*: The edges should be marked where the gradients of the image has large magnitudes.

The edge detection operator (Robert, Prewitt, Sobel for example) returns a value for the first derivative in the horizontal direction (Gx) and the vertical direction (Gy). From this the edge gradient and the direction can be determined:

$$\mathbf{G} = \sqrt{\mathbf{G}_x^{\ 2} + \mathbf{G}_y^{\ 2}}$$

$$\Theta = \operatorname{atan2}(\mathbf{G}_y, \mathbf{G}_x)$$

3. *Non-maximum suppression*: Only local maxima should be marked as edges.

4. *Double thresholding*: Potential edges are determined by thresholding.

5. *Edge tracking by hysteresis*: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

IV. LITERATURE REVIEW

*A.*To find different applications in image segmentation this paper [3] presented a new clustering-based segmentation technique. In image processing method clustering algorithm is widely used segmentation method but due to occurrence of noise during image acquisition, this might affect the processing results. In order to overcome this drawback, the proposed algorithm called Denoising-based(DB) clustering algorithm presented three variations namely, Denoising-based-K-means (DB-KM), Denoising-based-Fuzzy C-means (DB-FCM), and Denoising-based-Moving K-means (DB-MKM) [3]. This algorithm was proposed to minimize the salt-and-pepper noise without degrading the fine details of the images during the segmentation process. These methods incorporated a noise detection stage to the clustering algorithm, producing an adaptive segmentation technique specifically for segmenting the noisy images [3]. In this paper authors introduced a version of adaptive clustering based segmentation techniques. The basic concept behind this technique was to remove impulsive noises i.e., Salt-and-Pepper noise. Salt-and-Pepper noise contaminations, caused by errors in the image acquisition/recording/or transmissionare detectable at the minimum and maximum intensities. It is important to eliminate Salt-and-Pepper noise contained in theimage because its occurrence severely damage the information or data embedded in original image. Conventionally, in case of occurrence of Salt-and-Pepper noise in images we have to apply a pre-processing task like filtering before segmentation. To tackle this problem, they proposed an adaptive clustering-based segmentation techniqueby incorporating the noise detection stage for segmenting noisy images. The inherited noise detection behavior improved thesegmentation results by only selecting noise-free pixels for the process of segmentation. The result of this proposed algorithm was better when compared with conventional algorithms because of the inclusion of the noise detection stage in its process. Simulation results showedthat the proposed algorithms were able to remove low density of salt-and-pepper noise (i.e., up to 50%) during the segmentation process. This finding is proven by smaller values of F(I), F’(I), Q(I), and E(I) produced by the proposed DB-clustering algorithm [3]. This finding concluded the DB-clustering as a good technique for segmentation of noisy images, which could be used as pre- or post-processing technique inthe consumers’ electronics fields.

B. In study of coherent imaging systems for e.g. ultrasound and laser imaging, multiplicative noise (also known as speckle noise)models are central. With respect to the standard Gaussian additive noise scenario these models have two additional layer of difficulties: 1) the noise is multiplied by (rather than added to) the original image; 2) the noise is not Gaussian, with Rayleigh and Gamma being commonly used densities [4].In this paper author performed a set of experiments and presented that their proposed method named MIDAL (multiplicative image denoising by augmented Lagrangian), yields state-of-the-art results in terms of speed as well as in denoising performance.
In this paper [4], they addressed the (unconstrained) convex optimization problem results from the –look multiplicative model formulated with logarithm of the reflectance. An optimization algorithm is proposed with these respective building blocks:

- The original unconstrained optimization problem is firsttransformed into an equivalent constrained problem, via avariable splitting procedure that is described in [4];
- This constrained problem is then addressed in [4] using an augmented Lagrangian method.

*C.*Author of this paper [5] proposed a recursive filter, called the Cluster-based Adaptive Fuzzy Switching (CAFSM)for removing impulse noise from digital images. This filter is composed of a cascaded easy to-implement impulse detector and a noise filter (for detail preserving restoration). During digital images acquisition process images are commonly get contaminated with impulse noise. Hence, they focused on developing a robust filter that provide denoising for any type of impulse noise models. The CAFSM filter operates at a wide range of impulse noise densities without affecting image fine details and textures. They developed a fast and automated algorithm. In their simulation results they showed that the CAFSM filter outperforms other state-of-the art impulse noise filters in terms of subjective and objective qualities in the filtered images when applied recursively anditeratively and shows excellent restoration results in denoising color images [5].
The advantage of this proposed filter is its capability in handling realistic impulse noise model for real world application and regarded as a universal impulse noise filter. Fuzzy reasoning is embedded as part of its filtering mechanism. Extensive simulation results verified its excellent impulse detection and detail preservation abilities by attaining the highest PSNR and lowest MAE values across a wide range of noise densities shown in [5].
*D.*In this paper [6] authors proposed a general methodology (PURE-LET) for denoising images that are corrupted by mixed Poisson-Gaussian noise. This methodology is used for designing and optimizing a wide class of transform

domain thresholding and gives a competitive solution for fast and high-quality denoising of real fluorescence microscopy data. They expressed the denoising process as a linear expansion of thresholds (LET) that they optimized by relyingon a purely data-adaptive unbiased estimate of the mean-squarederror (MSE), derived in a non-Bayesian framework (PURE:Poisson–Gaussian unbiased risk estimate) [6]. They provided a practicalapproximation of this theoretical MSE estimate for the tractableoptimization of arbitrary transform-domain thresholding.

The two predominant source of noise in digital image during acquisition are:

- The random nature of the photon-countingprocess at the detectors;
- The intrinsic thermal and electronic fluctuations of the acquisition devices.

In the above given source of noise second source of noise, which is signal-independent, is stronger than the first one. This condition motivated the usual additive-white-Gaussian-noise (AWGN) assumption and the computational efficiency of this approach was resulted from the combination of the following two key ingridients:

1) A prior-free unbiased estimate of the expectedmean-squared error (MSE) between the unknown original image and the denoised one. Under an AWGN hypothesis, this estimator is known as Stein's unbiased risk estimate (SURE), while, for Poisson data, we called it PURE, which stands for Poisson's unbiased risk estimate [6].

2) A linear parameterization of the denoising process, through a linear expansion of thresholds (LET). The optimal parameters of this expansion are then the solution of a system of linear equations, resulting from the minimization of the sub-band-dependent quadratic unbiased estimate of the MSE [6].

In this paper they extended the PURE-LET approach in threemain directions described in [6] in detail:

- They lifted the restricted use of the unnormalized Haar wavelet transform by generalizing to arbitrary (redundant) transform-domain (nonlinear) processing.
- They considered a realistic noise model: A Poisson random vector degraded by AWGN, for which a theoretically unbiased MSE estimate was derived by them called PURE (combines both SURE and PURE).
- At last they showed that PURE can be used to globally optimize a LET spanning several (redundant) bases.

Further they defined a generic PURE LET framework for designing and optimizing transform-domain nonlinear processing.A first-order Taylor-series approximation of PURE was proposed in [6] by them to obtain a computationally fast and efficient algorithm for undecimated filter bank transforms.

E. In this paper [7] a new fuzzy switching median filter using fuzzy techniques was developed to remove salt-and-pepper noise from digital images preserving its details and textures as well. Some modifications have been made to improve this proposed filter. This FSM filter was composed of two semi-dependent modules:

- Salt-and-pepper noise detection module discussed in [7].
- Fuzzy noise cancellation module discussed in [7] (noise cancellation fuzzy set does not require time-consuming tuning of parameters and thus no training scheme is required).

In FSM salt-and-pepper noise can be either positive or negative. Positive impulse appears as white points (255 value) and negative as black (0 value). They defined a probability range for low level salt-and-pepper from 0 to .25 and for high level of salt-and pepper noise it was greater than or equals to .45 otherwise, the image is said to be corrupted by a moderately high level of salt-and-pepper noise.This FSM is an extension to the classical switching median filter by using fuzzy techniques. This proposed method was simple and of low complexity unlike some filtering mechanisms having iterations and lengthy processing time.

*F.*3D images are getting day by day popular in various applications including magnetic resonance imaging (MRI) and functional MRI (fMRI). Hence, 3D image denoising is often a necessary preprocessing step. We mostly have 2D denoising procedures in literature and their direct extensions to 3D cases are not much efficient because 3D images are substantially more complicated. Therefore, for 3D image denoising authors of this paper proposed a procedurewhich was based on local approximation of the edge surfaces using a set of surface templates. Their proposed method runs in the following three steps and explained in detail in [8]:

- Edge voxels are detected [8] using a 3D edge detector that is constructed under the JRA framework.
- Underlying edge surfaces are approximated in [8] in a neighbourhood of a given voxel by a surface template chosen from a pre-specified surface template family.
- 3D image denoising by estimating the true image intensity at the given voxel by using weighted average of the observed image intensities in the neighbourhood whose voxels are located on the same side of the surface template at the given voxel [8].

At last they did a numerical study in [8] and concluded that it performs favorably compared to several existing methods in various cases.

*G.*Generalized Gaussian Distribution (GGD) includes Gaussian and Laplace distributions and it is a symmetric distribution. GGD is widely used in modeling various types of signals in applications like image processing, speech processing and biomedical applications. One of the important challenges in analysis of GGD is denoising the available data. Author of this paper [9] studied behavior of the Bayesian estimator for noisy General Gaussian Distributed (GGD) data and focused on denoising GGD signals corrupted with additive Gaussian noise and also showed that this estimator can be estimated well with a shrinkage function. They investigated possible connections between the Bayesian estimator and thresholding. The main motivation was to analyze GGD and discovery of anymissing bridge between this optimum estimator and suboptimal thresholding methods (soft and hard). Their analysis showed that the GGD Bayesian estimator can be well modeled by a continuous piecewise linear cost functions with four parameters that is denoted by Rigorous Bayes Shrink (R-BayesShrink) [9]. Their work runs in given below steps:

- Problem formulation showed in [9].
- Estimation computation in [9] of GGD Bayesian Estimator.
- Rigorous BayesShrink estimation [9] with computational complexity.

They concluded that Bayesian estimator for GGD that behaves similar to R-BayesShrink and this estimator can be well approximated by soft thresholding map for when the parameter value lies in between 0.5 and one. Finally they succeeded in evaluation of their proposed method with four different data sets and showed that Shrinkage function can provide better PSNR for all the scenarios and also results in better edge preservation for image denoising.

V. CONCLUSION

In this paper, we explored some of the denoising techniques for image denoising. Here we analyzed and present a literature review of some of the proposed denoising techniques that will be useful for the users by getting a brief introduction of these techniques so that they can make use of any one of them if needed. Image processing is a widely growing field as many of the nowadays applications are making use of it. Therefore, there is also a need of image denoising techniques due to introduction of noisy elements during image acquisition. Hence, our concern is to provide a collective brief review of some of these techniques in a single paper to provide ease to the image users. Further our work is to implement an optimal fuzzy based noise removal technique for removing noise from colored images that will be explained with details in next paper.

VI. REFERENCES

[1] http://en.wikipedia.org/wiki/Image_noise
[2] Rafael C. Gonzalez, Richard E. Woods, "Digital Image Processing", 3rd edition, Pearson Education, 2008. [3] Siti Noraini Sulaiman, Nor Ashidi Mat Isa,"Denoising-based Clustering Algorithms for Segmentation of Low Level Salt-and-Pepper Noise-Corrupted Images,"IEEE Transactions on Consumer Electronics, Vol. 56, No. 4, pp. 2702-2710, November 2010.
[4] José M. Bioucas-Dias, Mário A. T. Figueiredo, "Multiplicative Noise Removal Using Variable
Splitting and Constrained Optimization," IEEE Transactions on Image Processing, vol. 19, No. 7, pp. 1720-1730, July 2010.
[5] Kenny Kal Vin Toh, Nor Ashidi Mat Isa, "Cluster-Based Adaptive Fuzzy Switching Median Filter for Universal Impulse Noise Reduction," IEEE Transactions on Consumer Electronics, Vol. 56, No. 4, pp. 2560-2568, November 2010.
[6] Florian Luisier, Thierry Blu, Michael Unser, "Image Denoising in Mixed Poisson–Gaussian Noise," IEEE Transactions on Image Processing, Vol. 20, No. 3, pp. 696-708, March 2011.
[7] Kenny Kal Vin Toh, Haidi Ibrahim, Muhammad Nasiruddin Mahyuddin, "Salt-and-Pepper Noise Detection and Reduction Using Fuzzy Switching Median Filter," IEEE Transactions on Consumer Electronics, Vol. 54, No. 4, pp. 1956-1961, November 2008.
[8] Peihua Qiu and Partha Sarathi Mukherjee, "Edge Structure Preserving 3D Image Denoising by Local Surface Approximation," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 34, No. 8, pp. 1457-1468, August 2012.
[9] Masoud Hashemi, Soosan Beheshti, "Adaptive Bayesian Denoising for General Gaussian Distributed Signals," IEEE Transactions on Signal Processing, Vol. 62, No. 5, pp. 1147-1156, March 1, 2014