# HRFA NOISE REMOVAL AND SEGMENTATION: A REVIEW

AUTHOR 1: K.M.HEMAMBARAN, RESEARCH SCHOLAR,
ECE DEPARTMENT, RAYALASEEMA UNIVERSITY, KURNOOL.
AUTHOR 2: Dr. S.A.K. JILANI, PROFESSOR, MITS, MADANAPALLE.

**ABSTRACT**

Processing an image is the method of exploring and manipulating a digitized image to recuperate the significant information of the image. Removal of corrupted data from the image is an major task in digital image processing. This paper presents a review on diverse techniques of image denoising and segmentation including 2D NHA. The 2D Non-Harmonic Analysis (2D NHA) is a high-resolution frequency estimation method that enhances noise exactness due to its side-lobe diminishing feature. The segmentation of corrupted images includes fuzziness in the selection of the region boundary. We believe that these fuzzy boundaries should be defined as edge areas.. The execution of NHA de-noising is necessary to approach the point of confinement of PSNR by enhancing the segmentation technique.

**Index terms:** image processing**,** diverse techniques, 2D-NHA, segmentation, edge regions.

## 1. INTRODUCTION

Computerized images assume an essential part both in everyday life applications, for example, satellite TV, resonance imaging, PC tomography and in addition in zones of research and innovation, for example, land data systems and stargazing. Informational indexes collected by image sensors are corrupted by the presence of Noise. Flawed instruments, troubles with the data protecting procedure, and interfering natural phenomenon would all be proficient to corrupt the information of intrigue. Besides, representation of noise can be made by transmission defects and compression. Subsequently, denoising is frequently an essential and the foremost step to be taken mainly before the image information is examined. It is significant to apply a proficient denoising method to avoid noise [3]. Noise in image directly degrades the visual quality, and also affects the performance of further processing such as edge and feature detection. The objective of image denoising methods is to estimate a clean image from its noisy observation [30].

The general thought is to assess a perfect image from the watched noise image. Large portion of denoising strategies are designed for expelling either Gaussian or impulse noise, which are substantially easier than the mixed noise removal. These two kinds of noise influence the image in very different ways, prompting diverse denoising techniques. For Gaussian noise removal, the normally utilized strategies incorporate total variation techniques and wave-let shrinkage approaches. The principle disadvantage of the total variation strategies is that the texture data in images could be constantly over-smoothed. In spite of the fact that the wavelet shrinkage techniques perform much better for texture preserving, they may show pseudo-Gibbs phenomena and acquire antiquities the recovered image [4]. Dan Zhang [2017], experimented a method of building realistic low-light image dataset. After that, he used an effective neural network based approach to solving low-light image denoising problem. Using a few images he collected in low-light environments by a cell phone, the presented neural network model is directly trained for removing noise from the noisy image patch [30]. Finally Hicham Badri [2016], introduced a novel method of image denoising based on the principle of non-local low-rankness transfer (LRT). Instead of using shrinkage operators to apply on the non-local singular values, we learn a mapping using a simple but efficient training model. This approach can support various types of corruption.
Amir Beck[2009], introduced novel gradient-based techniques for the controlled complete variation based image denoising problems. According to him the structure is common enough to cover up other categories of non-smooth regularizers and remains the ease of first order methods, and within a keen analysis which relies on adding a dual approach with a high-speed gradient projection format [2]. As per Julien Mairal[2013], the K-SVD has been developed to exploit the temporal correlation in video signals to rise the de-noising concert of the algorithm, providing for removing white Gaussian noise[8]. Publish of Lei Zhang [2010] concluded a competent PCA-based de-noising technique with local pixel grouping (LPG). PCA is an established de-correlation method in signal processing and it is unavoidably utilized as a part of pattern recognition and diminishing the dimensionality.

All these techniques illustrate better denoising performance than the conventional WT-based denoising techniques [11]. Image segmentation is a vast topic in the field of image processing and as well it is a hotspot and focal point of image processing schemes. A few numbers of collectively useful algorithms and techniques have been emerged for image segmentation. Since there is no particular result for the image segmentation problem. These methods repeatedly joined with domain knowledge in order to take care of an image segmentation problem for a problem domain [6]

## 2. TYPES OF NOISE MODELS

Noise defines presence of undesirable information in digitalized images. Noise produces unwanted impacts, for example, artifacts, unrealistic edges, concealed lines, corners, obscured objects and distracts background scenes. To minimize these unwanted impacts, earlier learning of noise models is fundamental for additional data processing. Probability density function (PDF) or Histogram is additionally practiced to describe and demonstrate the noise models. Here we can speak approximately couple of Noise models, their kinds and modules in virtual images.

### 2.1 Gaussian Noise Model

Gaussian noise is called as electronic noise since it comes out from amplifiers or detectors. Gaussian Noise is produced by usual resources, as an example, thermal vibration of atoms and different nature of emission of heat objects largely differentiates the gray values in digital images. That is the rationale why Gaussian Noise model basically outlined and defined via its PDF or standardizes histogram concerning gray values. This is given as

$$\boldsymbol{P(g)} = \sqrt{\frac{\mathbf{1}}{\mathbf{2\pi\sigma^2}}}\,\boldsymbol{e}^{\frac{-(g-\mu)^2}{2\sigma^2}}$$

Where g = gray value, σ = standard deviation and μ = mean. For most of the elements Gaussian Noise statically illustration relies to the ideal approximation real world situations. In this noise model, the imply value is zero, variance is 0.1.

### 2.2 White Noise

Corruption of data by the noise is mostly varied by the noise power. Noise power range is general in white noise. This noise power is the same as the power spectral density characteristic. The be aware "Gaussian Noise is regularly white noise" is wrong. Anyway neither Gaussian belonging initiates the white noise. The limitation of collective noise power is - ∞ to +∞ to be in white noise in frequency domain. It entails that the noise strength is infinite in white noise. The possibility of correlation in white noise is due to the reason that each pixel values are unique in relation to their neighbors. This is the limitation for which the auto correlation becomes zero. So the pixels also disturb positively because of white noise.

### 2.3 Fractal Noise (Brownian Noise)

Colored noise can be called with diverse names, at an instance, Brownian noise or glint noise or pink noise or 1/f noise. Production of fractal noise can be done by utilizing the Brownian motion, Fractal motion which is visible because of the irregularities of suspended units in fluid. This is the procedure to generate fractal noise from white noise. This noise pursues non stationary stochastic structure as well as the ordinary distribution. So that obviously fractional Brownian Noise is known as fractal noise. Gaussian method is different from this noise.

### 2.4 Impulse Valued Noise (Salt and Pepper Noise)

This type of noise is called as records drop noise due to the reason that it diminishes the authentic facts values. This kind of noise can also be called as salt and pepper Noise. This noise does not degrade the image to a huge extent as an alternative few of the pixel values are residue distorted in the image. In spite of that in a noisy image a few of the pixels do not alter. This noise is present in the data transmission. Here the image pixels are replaced by the corrupted pixel values by both extreme 'or' least pixel value i.e., 255 'or' 0 respectively.

### 2.5 Temporal Noise

Temporal Noise differs at random each time an image is captured. Due to this noise the performance of image sensor will be degraded, especially under low light and in video applications. In a CCD image sensor, this noise occurs due to the photo detector and the output amplifier [4]

## 3. DIFFERENT ALGORITHMS FOR DENOISING

### 3.1 Denoising By Exploring both Internal and External Correlations

As indicated by Huanjing Yue[2015], Single image denoising experiences restricted data accumulation within the noise corrupted image. So he evaluated a novel image denoising method, which examines both inner and outside correlations with the assistance of web images. For each noise patch, he made inward and outer data cubes by finding relevant patches from the noisy and web images, separately. By joining the inner and outer denoising patches, he acquired a preliminary denoising result. In the second stage, we propose decreasing noise by separating of outside and inside cubes, separately, on transform domain [9]

### 3.2 Non-Local Similarity Regularizer

Shuyuan Yang [2013], proposed both the similarity prior and random prior of images, and proposed a dictionary learning and non-local similarity regularizer based noise removal approach. By defining the image noise reduction as a different factor of optimization problem, he proposed another algorithm to then again improve the variables[14].

### 3.3 High Resolution Frequency Analysis

Finally Toshio Yoshizawa [2011], declared that NHA gives high frequency resolution by excluding the impact of the window length. The drawback to the accurate enhancement of noise suppression by NHA is checked. Since a frequency range using NHA isn't inclined by the window length at the time of frequency change, the frequency resolution width is viewed as theoretically minute [17].

### 3.4 Block Matching and 3-D Filtering (BM3D)

According to Vladimir Katkovnik [2010], in BM3D algorithm, the utilization of the indicator window describes the nonlocal support while the specificity of the comparative weighting of these windows are disregarded. Under this simplification, all basic aspects of the algorithms are similar to the ones of standard transform-domain filtering [7].

We reviewed all the algorithms and to overcome the drawbacks of the above algorithms we proposed a novel algorithm for the removal of zero-mean white Gaussian noise that is 2D non- harmonic analysis (2D-NHA) which is a high-resolution frequency analyzing method that enhances noise exclusion accuracy on account of its side-lobe diminished feature.

High- resolution frequency analysis technique called non-harmonic analysis (NHA) [17]. NHA has been utilized as a part of various applications and conveys satisfactory results. It enhances thresholding accuracy since it communicates frequency using a line spectrum that can reduce the side-lobes

Using a large analysis window enhances the frequency resolution of DFT and DCT but reduces their spatial resolution. NHA can attain a frequency of satisfactory resolution with a relatively small window due to the reason that it does not depend on the range of the analysis window. NHA imagines a standard signal in the analysis window. Therefore, non-stationarity in the analysis window produces a sidelobe during frequency analysis. The 2D NHA estimates frequency by diminishing the mean squared error (MSE) between the target signal and the model signal, and is calculated by the technique of steepest descent.

The original signal can be distorted by the reduction of the side-lobe through thresholding. This is the obstacle to denoising. NHA can suppress sidelobes by the usage of high frequency resolution. High-frequency resolution analysis can distinguish the original signal from the noise signal. Image denoising using domain transformation often employs a block unit called a "patch." The smoothing effectiveness of denoising increases with the patch size. However, the likelihood of the edge mixing with the patches increases when using large patches. The edge is transformed into the sine function by DFT. When part of the sinc function in the frequency domain is removed by thresholding, the restored image includes a ringing artifact. The edge details are hence lost by thresholding because sidelobes always takes place as a effect of the analysis of edges. Hence, denoising requires to be applied to stationary signals to avoid detail deletion.

## 4. EDGE DETECTION AND SEGMENTATION

Edge detection methods change images to edge images using the transforms of grey tones in the images. Edges are the indication of lack of continuity, and ending. An edge determines the boundaries between regions in an image, which helps with segmentation and object recognition. Edge detection of an image significantly diminishes the amount of data and filters out undesirable data, by preserving the important structural properties in an image [18].

Publish of P. Sujatha [2015], analysed the performance analysis of various edge detection techniques. Then finally concluded that Prewitt shows better output than Sobel and Roberts on the basis of intensity values. While Sobel presents a superior approximation to gradient magnitude, it finds the edges containing highest gradient. Since the filter is small, Roberts generates consequences very rapidly than Sobel and Prewitt. Finally from the above analysis, it is seen that each operator is considered as the best under different scenarios. In future, apart from the aforementioned operators, edge detection will be done out with some other operators such as Canny, Laplace of Gaussian for the images set [22].

In [24] a technique toward the detection of perceived ringing regions in compressed images is presented. The algorithm relies on the compressed image only, which is capable for its usage in a real-time video chain, e.g., to increase the quality of artifact impaired video. It assumes a perceptually more meaningful edge detection technique for the idea of ringing region location. This intrinsically avoids the problem of applying an normal edge detector.

In [25] C. Tomasi introduced Bilateral filtering which smoothes the images while safeguarding edges, by methods of nonlinear merge of nearby image values. The technique is non-iterative, local, and less complex. It merges grey levels or colors on basis of both their geometric proximity and their photometric resemblance and persuades toward near values to far values in both space and range. In disparity with filters that functions on the three bands of a color image independently, a bilateral filter can implement the perceptual metric essential for the CIE-Lab color space, and levels the colors and conserve edges in a way that is altered to human perception.The drawback of bilateral filters is harder to analyze than domain filters, because of their nonlinear nature.

As per Mei Fang[2009], Canny algorithm can be utilized as a part of separating the object's shape obviously by setting the proper parameters. The Otsu algorithm can calculate the high edge value which is significant to the Canny algorithm, and after that this threshold value can be utilized as a part of the Canny algorithm to recognize the objects edge and has improved the effect of edge extraction [29].

Canny edge detection by using bilateral filtering which improves the accuracy. Canny edge detection [23], which is commonly used to identify edge position. It uses a smoothing process prior to edge detection. The smoothing method often uses a Gaussian filter, but this distorts the edge position if it is used in Canny edge detection. To begin with we separated the edges from a noise image. At that point the edge regions can be expelled by the binary dilation of edges from the noisy image. Segmentation is the procedure that subdivides an image into its constituent parts or protests by preserving the edges.

Two of the most important low level vision operations are image segmentation and edge detection [26]. Because of the prevailing computer generation image processing strategies have turned out to be an increasing number of necessary in a huge variety of packages. Image segmentation is a standard problem in the region of image processing and also it is a hotspot and view factor of image processing strategies. A few largely beneficial algorithms and strategies have been produced for photo segmentation. Since there may be no finite elucidation for the image segmentation issue, these techniques often mixed with area expertise a good way to proficiently decide an image segmentation quandary for a problem domain [6]

Nida M. Zaitoun [2015] concluded that block image segmentation methods are two main categories: region based and edge or boundary based method and each one of them is separated into numerous techniques. The image is segmented using a series of decision and there is no universal segmentation method for all kinds of images and also an image can be segmented by using different segmentation methods [6].

However, the boundary definition of each region with uniform texture is difficult to provide using existing segmentation methods. Thus, it is difficult to find the boundary of a region within a noisy image. In particular, the segmentation of a noisy image often causes errors. Therefore, the segmentation of noisy images contains fuzziness in the choice of the region boundary. Therefore in our review it is explained that first extract the edges from a noisy image and then define the edge regions. Boundary distortion due to segmentation is reduced by defining the texture boundaries. Region growing is a technique to iteratively expand the initial region, and region merging combines the over-segmented results. These methods cannot be used without subsequent information of the image in question. The mean shift algorithm searches for local maximum density points in a feature space [27]. Moreover, mean shift does not require information regarding the number of segments. For the analysis of segmented images, 2D-NHA needs to be adapted to nonrectangular windows.

## 5. CONCLUSION

The noise in the image can decrease the quality of the image. So that, by reviewing all the denoising algorithms and segmentation methods for the removal of the noise 2D non-harmonic analysis (2D-NHA) followed by edge preserved segmentation is better. It is concluded that the 2D NHA techniques is better than the conventional techniques in the case of noise removal from the image to a great extent. The enhancement of the quality of image can be done after applying this method. It is expected that the Non uniform regions that occur in an image due to Segmentation are analysed by an extended methods which improves the PSNR|(Peak Signal to Noise Ratio).

## 6. REFERENCES

[1] J. Mairal, M. Elad, and G. Sapiro, "Sparse representation for color image restoration," *IEEE Trans. Image Process.*, vol. 17, no. 1, pp. 53–69, Jan. 2008.

[2] A. Beck and M. Teboulle, "Fast gradient-based algorithms for constrained total variation image denoising and deblurring problems," *IEEE Trans. Image Process.*, vol. 18, no. 11, pp. 2419–2434, Nov. 2009.

[3] Dr Balkrishan, Harmandeep singh and Gurjeet Kaur "A Review on Image Denoising Methods ," IJAEGT., vol. 3, Issue 11, pp. 2309-4893 , December 2015.

[4] H. Tian, B. Fowler, and A. El Gamal, "Analysis of temporal noise in CMOS photodiode active pixel sensor," *IEEE J. Solid-State Circuits*, vol. 36, no. 1, pp. 92–101, Jan. 2001.

[5] K. Hirakawa and T. W. Parks, "Image denoising using total least squares," *IEEE Trans. Image Process.*, vol. 15, no. 9, pp. 2730–2742, Sep. 2006.

[6] Nida M. Zaitoun, and Musbah J. Aqel**, "**Survey on Image Segmentation Techniques," published by Elsevier , Jan. 2015.

[7] V. Katkovnik, A. Foi, K. Egiazarian, and J. Astola, "From local kernel to nonlocal multiple-model image denoising," *Int. J. Comput. Vis.*, vol. 86, no. 1, pp. 1–32, 2010.

[8] C. Loader, *Local Regression and Likelihood*. New York, NY, USA: Springer-Verlag, 1999, vol. 47.

[9] M. Elad and M. Aharon, "Image denoising via sparse and redundant representations over learned dictionaries," *IEEE Trans. Image Process.*, vol. 15, no. 12, pp. 3736–3745, Dec. 2006.

[10] Ajay Kumar Boyat and Brijendra Kumar Joshi, "Noise Models In Digital Image Processing," SIPIJ, Vol.6, No.2, April 2015
[11] L. Zhang, W. Dong, D. Zhang, and G. Shi, "Two-stage image denoising by principal component analysis with local pixel grouping," *Pattern Recognit.*, vol. 43, no. 4, pp. 1531–1549, 2010.
[12] A. Buades, B. Coll, and J. M. Morel, "A review of image denoising algorithms, with a new one," *Multiscale Model. Simul.*, vol. 4, no. 2, pp. 490–530, 2005.
[13] K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative filtering," *IEEE Trans. Image Process.*, vol. 16, no. 8, pp. 2080–2095, Aug. 2007.
[14] S. Yang, L. Zhao, M. Wang, Y. Zhang, and L. Jiao, "Dictionary learning and similarity regularization based image noise reduction," *J. Vis. Commun. Image Represent.*, vol. 24, no. 2, pp. 181–186, 2013.
[15] O. G. Guleryuz, "Weighted averaging for denoising with overcomplete dictionaries," *IEEE Trans. Image Process.*, vol. 16, no. 12, pp. 3020–3034, Dec. 2007.
[16] Tanzila Rahman, Mohammad Reduanul Haque, Liton Jude Rozario and Mohammad Shorif Uddin, " Gaussian Noise Reduction in Digital Images Using a Modified Fuzzy Filter," 78-1-4799-6288-4/14
[17] T. Yoshizawa, S. Hirobayashi, and T. Misawa, "Noise reduction for periodic signals using high-resolution frequency analysis," *EURASIP J. Audio, Speech, Music Process.*, vol. 5, no. 5, pp. 1–19, 2011.
[18] Pooja Sharma,Gurpreet Singh and ,Amandeep Kaur, " Different Techniques Of Edge Detection In Digital Image Processing," IJERA, Vol. 3, Issue 3, May-Jun 2013, pp.458-461
[19] X. Cao *et al.*, "Non-harmonic analysis applied to optical coherence tomography imaging," *Jpn. J. Appl. Phys.*, vol. 51, no. 2R, p. 022503, 2012.
[20] T. Ueda, K. Fujii, S. Hirobayashi, T. Yoshizawa, and T. Misawa, "Motion analysis using 3D high-resolution frequency analysis," *IEEE Trans. Image Process.*, vol. 22, no. 8, pp. 2946–2959, Aug. 2013.
[21] P.Chatterjee and P. Milanfar, "Clustering-based denoising with locally learned dictionaries," *IEEE Trans. Image Process.*, vol. 18, no. 7, pp. 1438–1451, Jul. 2009.
[22] P. Sujatha and K. K. Sudha, " Performance Analysis of Different Edge Detection Techniques for Image Segmentation," Indian Journal of Science and Technology, *Vol 8(14), DOI: 10.17485/ijst/2015/v8i14/72946, July 2015*
[23] J. Canny, "A computational approach to edge detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 8, no. 6, pp. 679–698, Nov. 1986.
[24] H. Liu, N. Klomp, and I. Heynderickx, "A perceptually relevant approach to ringing region detection," *IEEE Trans. Image Process.*, vol. 19, no. 6, pp. 1414–1426, Jun. 2010.
[25] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in *Proc. 6th Int. Conf. Comput. Vis.*, Jan. 1998, pp. 839–846.
[26] D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 5, pp. 603–619, May 2002.
[27] K. Fukunaga and L. Hostetler, "The estimation of the gradient of a density function, with applications in pattern recognition," *IEEE Trans. Inf. Theory*, vol. 21, no. 1, pp. 32–40, Jan. 1975.
[28] C. M. Christoudias, B. Georgescu, and P. Meer, "Synergism in low level vision," in *Proc. 16th Int. Conf. Pattern Recognit.*, vol. 4. 2002, pp. 150–155.
[29] H.-Q. Li, Q.-C. Yu, and M. Fang, "Application of otsu thresholding method on canny operator," *Comput. Eng. Design*, vol. 9, p. 046, 2008.
[30] Dan Zhang, Lei Zhao, Duanqing Xu, Dongming Lu, "A Neural Network Based Low-Light Image Denoising Method," IEEE International Conference, 978-1-5090-6352, Dec.2017
[31] Hicham Badri, Hussein Yahia and Driss Aboutajdine, "Low-Rankness Transfer for Realistic Denoising," *IEEE Trans. Image Process,* vol. 25, no. 12, pp. 1057-7149, Dec.2016