# Estimation, Suppression and Optimization of Impulses in Digital Imagery

**Abstract submitted for the Degree of Doctor of Philosophy (Engineering) in the Faculty of Engineering, Technology and Management, University of Kalyani**

By


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## 0.1 Introduction

Image denoising is the problem of generating a clean image, given a noisy one. In most cases, it is assumed that the noisy image is the sum of an underlying clean image and a noise component. Hence image denoising is a decomposition problem: The task is to decompose a noisy image into a clean image and a noise component. Since an infinite number of such decompositions exist, one is interested in finding a plausible clean image, given a noisy one. The notion of plausibility involves prior knowledge: One knows something about images and about the noise. Without prior knowledge, image denoising would be impossible. Usually, it is impossible to find the clean image exactly. One is therefore interested in finding an image that is close to the clean image.

The goal of digital enhancement is to process an image where the resultant image is more suitable than the original image for a specific application. Image enhancement is one of the most interesting areas of image processing. Image enhancement approaches fall into two broad categories: spatial domain methods and frequency domain methods. The term spatial domain refers to the image plane itself, and approaches in this category are based on direct manipulation of pixels in an image where as frequency domain processing techniques are based on modifying the Fourier transform of an image. Beginning in the 1990s, wavelets have been found to be a powerful tool for removing noise from a variety of signals (denoising). They allow to analyze the noise level separately at each wavelet scale and to adapt the denoising algorithm accordingly.

During any physical measurement, it is likely that the signal is corrupted by some amount of noise. The sources and types of noise depend on the physical measurement. Noise often comes from a source that is different from the one to be measured, but sometimes is due to the measurement process itself. Sometimes, noise might be due to the mathematical manipulation of a signal, like image deconvolution or image compression. Often, a measurement is corrupted through several sources and usually difficult to characterize all of them fully. In all cases, noise is the undesirable part of the signal. Ideally, one seeks to reduce noise by manipulating the signal acquisition process, but when such a modification is impossible, denoising algorithms are required.

The characteristics of the noise depend on the signal acquisition process. Images can be acquired in a number of ways, including, but not limited to: Digital and analog cameras of various kinds (e.g. for visible or infra-red light), magnetic resonance imaging (MRI), computed tomography (CT), positron-emission tomography (PET), ultrasonography, electron microscopy and radar imagery such as synthetic aperture radar (SAR). Photon noise[1], also known as Poisson noise, is a basic form of uncertainty associated with the measurement of

[1] http://people.csail.mit.edu/hasinoff/pubs/hasinoff-photon-2012-preprint.pdf

light, inherent to the quantized nature of light and the independence of photon detections. Thermal noise arises due to the thermal energy of electrical and electronic devices. Gaussian noise [2] in digital images arises during acquisition for example sensor noise caused by poor illumination and/or high temperature, and/or transmission for example electronic circuit noise. Gaussian noise is evenly distributed over the signal. Each pixel in noisy image is the sum of true pixel value and a random Gaussian distributed noise value. There are two noise models available in literature. These are salt and pepper and random valued noise. Noise is modeled as salt-and-pepper noise (SPN), pixels are randomly corrupted by two fixed extreme values, 0 and 255 (for 8-bit monochrome image), generated with the same probability. Instead of two fixed values impulse noise could be more realistically modeled by two fixed ranges that appear at both ends with a length of m each respectively. That is known as Random valued noise (RVN).

Image quality [3] metrics are paramount to provide quantitative data on the fidelity of rendered images. Image quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Several image quality metrics have been developed whose goals are to predict the visible differences between a pair of images. Image quality can, however, also be related to the subjective perception of an image, e.g., a human looking at a photograph. The measures are Mean Square Error (MSE), Peak-Signal-to-Noise-Ratio (PSNR), Image Enhancement Factor (IEF) and Structure Similarity Index Measure (SSIM).

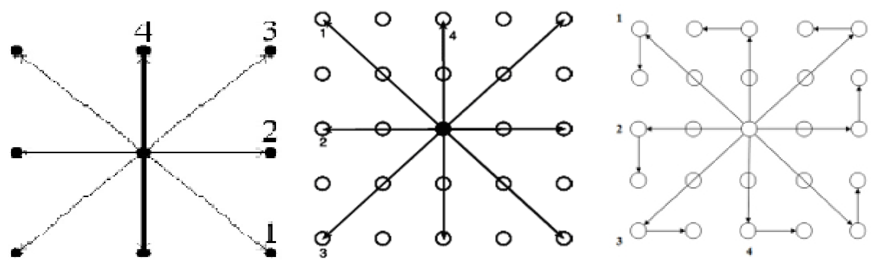
## 0.2 Proposed Denoising Techniques

In this section, algorithms for noise estimation, suppression and optimization in the digital and medical images have been proposed. Five categories of techniques are proposed in the spatial domain which are noise suppression, filter optimization, noise density estimation for adaptive median filter, PSO based clustering for noise detection and restoration and fuzzy switching median filter. In the frequency domain one wavelet transformation based noise suppression and optimization technique is proposed. In the noise suppression techniques, two types of algorithms are proposed such as deviation based filter and weighted median filter. Two algorithms are proposed in the category of deviation based filter which are based on simple statistical and mathematical operators, such as *Directional Weighted Minimum Deviation Filter* and *All Neighbor Directional Weighted Pixels Filter* for noise suppression. Three weighted median filters such as *Variable Mask Median Filter*, *Edge Preserving Restoration*

[2] http://en.wikipedia.org/wiki/Gaussian_noise
[3] http://en.wikipedia.org/wiki/Image_quality

*Filter* and *Sub-image based Restoration Filter* have been proposed for restoration of digital images. Two optimization algorithms based on *Genetic Algorithm (GA)* and *Particle swarm Optimization (PSO)* have been proposed for searching the user parameters in a wide range to obtain the optimal restoration results. An adaptive median filter based on estimation of noise density towards filtering window selection has also been proposed. A novel clustering algorithm for image denoising based on fixed and different length PSO based image clustering has been proposed in the thesis. A fuzzy switching median filter has also been proposed in spatial domain for image denoising. In the frequency domain, a wavelet transformation based technique is proposed which can suppress the mixed Gaussian and Poisson noises in the medical images. All of these methods are described below.

### 0.2.1 Noise Suppression




**(a)** **(b)** **(c)**

Figure 1: a, b and c represent $3 \times 3$, $5 \times 5$ and all neighbor $5 \times 5$ window regions

The working principal of these algorithms are based on simple statistical and mathematical operators. The noisy pixels in each test window are detected by the noise detection operator and then only the noisy pixels in each window are restored by a noise filtering operator. The test window size is $2m{+}1 \times 2m{+}1$, where m is a positive integer. The test window slides to nest pixel to consider the center pixel of the window in row major order. Each time the center pixel of the window is classified by the proposed noise detector and then the noisy pixels are filtered by using the neighboring pixels of the test pixel which has been detected as noisy by the noise detection rule. The noise free pixels are left unchanged.

The *directional weighted minimum deviation filter (DWMD)* assumes that a noise free image consists of locally smoothly varying areas separated by edges. The test window is given in Fig. 1 (b). The methodology is used for impulse detection based on simple arithmetic operation like the absolute differences between the center pixel and all other pixels in the test window. Then the minimum of the differences are selected and compared with a threshold (user parameter) to classify the center pixel. In the filtering stage, the optimal direction among the four in the test window has been selected. The center pixel of the optimal direction which has been detected as noisy, being updated to make the pixels most closely clustered. This has been done to make the set of pixels having minimum standard deviation.

The *all neighbor directional weighted pixels (ANDWP)* based filter has been proposed for removal of high density random valued noises (RVN) in the digital images. The test window is given in Fig. 1 (c). All neighboring pixels of the test window have been considered here. The proposed approach works in two phases. The first phase detects the contaminated pixels by making the differences between the test pixel and its all neighbor pixels aligned in four directions in the 5 × 5 window. The second phase filters only the noisy pixels based on minimum variance of the four directional pixels. The advancement done here compared to the previous method is considering all the neighboring pixels in the 5 × 5 window in both the stages of detection and filtering, secondly the variance based filter is optimized by the principal of finding the minima by using an algebraic equation.

Three techniques are proposed which are based on median filtering technique. The first method *variable mask median filter* uses all neighbor directional pixels in the 5 × 5 test window for impulse noise detection. Simple arithmetic absolute differences are computed and then the minimum among them is selected to compare with an user parameter *Threshold T* for classification of the center pixel in the test window. To filter the noisy pixels both the 5 × 5 and 3 × 3 (given in Fig. 1 (a)) masks are used and a median based filter has been proposed. For filtering it uses an improved median based filtering technique which uses variable mask consisting of nine and twenty five pixels respectively. Certain pixels in the 3 × 3 window are selected prior to compute median operation. Three user parameters viz., *number of iterations(I), threshold(T) and decreasing rate (R) of threshold in each iteration* are varied in a three dimensional space to obtain optimal results.

The *edge preserving restoration filter (EPR)* concentrates on *miss alarm rate* of the noise detection operator rigorously. The first step is to classify whether the center pixel in the 5 × 5 window is noisy or not, which is done using all neighbor directional weighted pixels in a 5 × 5 mask. The proposed algorithm performs simple arithmetic absolute differences on the pixels aligned in the four directions with the center pixel. On detection of noisy pixels an advance median filter has been proposed for restoration of noisy pixel where a variable window consisting of 3 × 3 and 5 × 5 respectively have been used. To optimize the results, a three dimensional search space has been used on user supplied parameters in a wide range.

*Sub-image based restoration (SIR)* filter is a novel approach which aims at detection and filtering of impulses in digital images through median filtering. The proposed detection method is based on all neighbor directional pixels. This method proposes a weighted median filter based impulse detection and suppression techniques in digital images. The training image is logically partitioned into several 5 × 5 window sub regions. Each of the window separately goes through two different masks such as $3 \times 3$ and $5 \times 5$ and produces two different restored versions of that window. Each of the restored versions is compared with the original to compare the fitness in terms of PSNR (dB). The correction obtaining maximum PSNR is accepted and incorporated in to the selected window. PSNR is calculated at end of restoration of all $5 \times 5$ sub window regions of the test image. Both $3 \times 3$ and $5 \times 5$ window based detection and filtering operators use all neighbor directional pixels to include all the pixels in the window. Four directions of the center pixel within are considered to classify the center pixel. Only noisy pixel goes through the filtering operator, the remaining pixels are not altered. The detection operator computes arithmetic operations on the directional pixels with the center pixel to define a noisy pixel. The filtering operator selects the most important directional pixels among the four to calculate the median value and that replaces the center pixel.

### 0.2.2 Filter Optimization

The noise removal operators discussed in the previous algorithms are optimized to get the global optimal restoration results. Two optimization algorithms which are stochastic and randomized in nature are used for optimization of the noise removal operators discussed so far. Three parameters viz., *number of iterations(I), threshold(T) and decreasing rate (R) of threshold in each iteration* of the detection and filtering operators are searched in a three dimensional space to find the optimal solutions using *Genetic Algorithm (GA)* and *Particle Swarm Optimization (PSO)* techniques based optimization algorithms.

### 0.2.3 Noise Density Estimation for Adaptive Median Filter

A novel approach is proposed which aims at detection and filtering of impulses in digital images through clustering of pixels. This approach coagulates directional weighted median filtering with unsupervised pixel classification based adaptive window selection for detection and filtering of impulses in digital images. K-means based clustering algorithm has been done to select an empirical window to detect and restore the noisy pixels. Estimation of noise density in an image has been done through *Laplasian operator* [4] in connection with simple arithmetic comparisons, which promotes to select proper window size for adaptive median filtering.

[4] http://mathworld.wolfram.com/Laplacian.html

### 0.2.4 PSO based Clustering for Noise Restoration

In this section, a denoising method has been proposed where the detection and filtering is based on clustering of image pixels. The noisy image is grouped into subsets of pixels with respect to their intensity values and spatial distances. *Fixed length particles swarm optimization (FPSO)* and *different length particles swarm optimization (DPSO)* based image clustering algorithms have been proposed. Using a novel fitness function the image pixels have been clustered by using FPSO and DPSO techniques. The proposed fitness function has evaluated three criteria such as *inter cluster distance, inter cluster distance and weighted quantization error* functions. The novel Euclidean distance function has measured the similarity/dissimilarity among the pixels using not only the intensity values but also the positions of the pixels in the image matrix. The detection technique has enforced the *PSO* based clustering techniques, which is very simple and robust. Filtering operator has restored only the noisy pixels keeping noise free pixels intact.

### 0.2.5 Fuzzy Switching Median Filter

In this section, a fuzzy based switching technique has been proposed which aims at detection and filtering of impulse noises from digital images. Two different types of noise models have been used to obtain the noisy images. In this two step process, the noise free pixels have been remained unchanged. The proposed detection algorithm has used $5 \times 5$ window, based on all neighboring pixels on the centered of the window of a noisy pixel. Two different weighted median filters have been devised and a particular one has been applied selectively to the noisy pixel based on the characteristics of the neighboring pixels within the window. Instead of a single threshold, two threshold values have been used in the proposed fuzzy membership (MF) function to partition the noise level and accordingly a filtering method has been applied to restore the corrupted pixel.

### 0.2.6 Denoising in Frequency Domain

Although the spatial filters perform well on digital images but they have some constraints regarding resolution degradation. These filters operate by smoothing over a fixed window and it produces artifacts around the object and sometimes causes over smoothing thus causing blurring of image. Wavelet transform is best suited for performance because of its properties like sparsity, multiresolution and multiscale nature. All frequency filters can also be implemented in the spatial domain and, if there exist a simple kernel for the desired filter effect, it is computationally less expensive to perform the filtering in the spatial domain. Frequency filtering is more appropriate if no straightforward kernel can be found in the spatial domain, and may also be more efficient.

This section proposed a technique which aimed to recover the original image $g(t)$ by removing the *Gaussian noise* and *Poisson noise* from the noisy image $f(t)$ with the mean square error (MSE) is minimum. The basis of wavelet based denoising is to transform the noisy image into the wavelet domain, threshold the wavelet coefficients, and perform the inverse wavelet transformation. The thresholding of wavelet coefficients in the transformed domain is followed using the Bayesian method and modification to the method has been performed in the proposed algorithm. An approach which is adaptive in sub band of wavelet decomposition has been devised in this algorithm. The most important parameter of wavelet decomposition is the level of decomposition. The proposed algorithm has searched the corrected threshold on the *Bayesian thresholding* and the value of the *decomposition level* using a stochastic and randomized search algorithm, i.e., *Genetic algorithm*. The input images have been corrupted using the additive white Gaussian and Poisson noises with a wide range of noise density and then applied to the proposed algorithm. *Genetic algorithm (GA)* based wavelet denoising has been proposed for optimization of the threshold value.

## 0.3 Experimental Results and Comparisons

In this section, the proposed algorithms are compared with the existing algorithms in terms of PSNR(dB), IEF and SSIM metrics. Two noise models are considered for making the noisy images. Those are *random valued noise (RVN)* and *salt and pepper noise (SPN)*. In case of noisy medical images corrupted by the mixed *Gaussian* and *Poisson* noises, the wavelet based denoising method is done. Results obtained from all the proposed filters on the spatial and wavelet domain are compared and validated by extensive simulation results, in this section. The required execution time for all the proposed algorithms are studied and compared with the state of the art algorithms in the literature. Variable noise densities from 10% to 100% have been applied to five bench mark images to evaluate the performances.

In Fig. 2, the proposed algorithms are compared to SMF, AMF, DWM, EDBA, IDBA, FBDA and NASRI algorithms. In this figure, all results are generated on the images corrupted by SPN. The *Average PSNR* values are shown in this figure for *Lena*, *Cameraman*, *Liftingbody*, *Boat* and *Barbara* images with different noise density from 10% to 100%. From this figure, it can be seen that for the entire spectrum of noise density, the proposed algorithm **DPSO** performs the best in terms of PSNR. The DPSO algorithm performs much better than the NDE algorithm in terms of quantitative restoration results. The FSMF performs better than NASRI for the noise densities such as 10%, 30%, 60%, 80%, 90% and 100%. For other noise densities, the FSMF is defeated by the NASRI filter. But DPSO filter performs the best than any algorithm in the figure in terms of PSNR. The NDE obtained much better PSNR than the FBDA filter but not NASRI. The FSMF filter has given slightly less PSNR than the DPSO filter. In Fig. 3, all results are generated on the images corrupted by RVN.

From this figure, it can be seen that for the entire noise density, the **DPSO** algorithm performs the best in terms of PSNR. The DPSO and FSMF filters obtained better PSNRs than any existing filters in the figure. The NDE filter obtained better PSNRs than NASRI for the noise densities, 10%, 20%, 30%, 70%, 90% and 100%. The FBDA filter performs better than ANDWP filter. From the figure, it is clear that the **DPSO** algorithm has obtained much better restoration results than the existing algorithms for the entire noise density. The algorithm also obtained better PSNR than other proposed filters such as DWMD, ANDWP, VMM, EPR, SIR, GASIR, PSOSIR, NDE and DPSO.

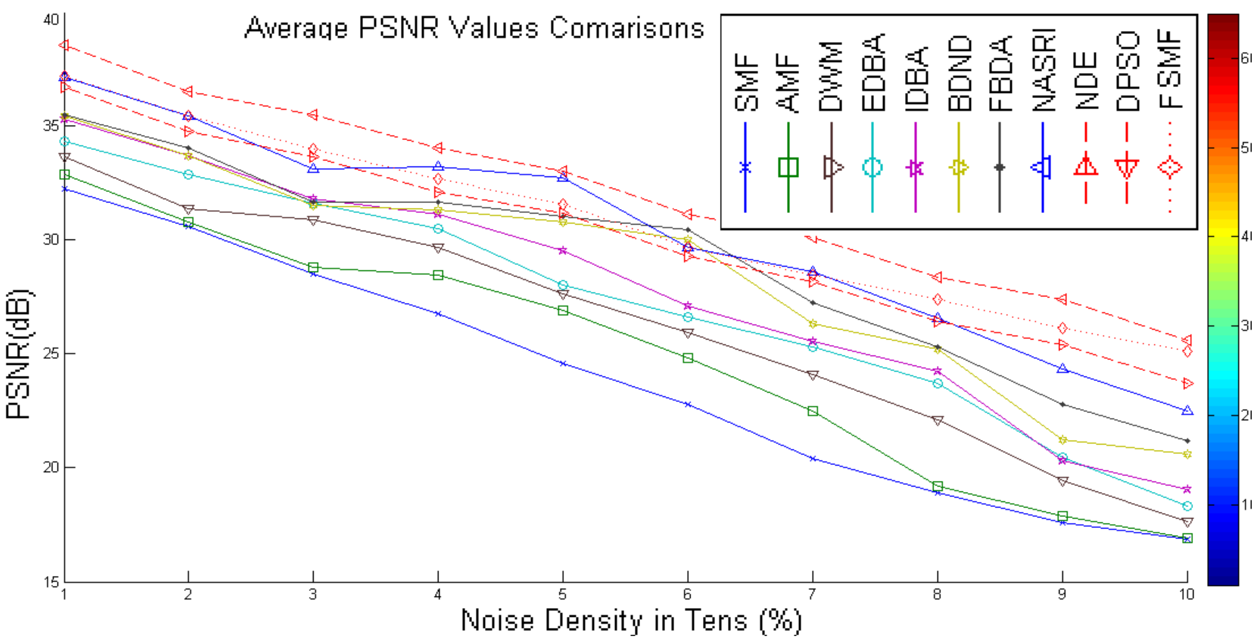



Figure 2: Graph of average PSNR values for *Lena*, *Cameraman*, *Liftingbody*, *Boat* and *Barbara* images for 10% to 100% SPNs by existing and **FSMF** filter

In Fig. 4, all results are generated on the images corrupted by SPN. The average IEF values are shown in this figure for five images. From this figure, it is seen that for the entire noise density, **DPSO** algorithm performs the best in terms of IEF. The SMF and AMF perform very poor. The NASRI obtained better IEF than the NDE for only 10% noise density. For all other cases, NDE performs better than NASRI. The FSMF filter performs much better restoration results than any existing algorithms. The DPSO performs much better than FSMF filter. In Fig. 5, all results are generated on the images corrupted by RVN. The *Average IEF* values are shown in this figure. From this figure, it can be shown that for the entire noise density, the algorithm **DPSO** performs excellent in terms of IEF compared to any algorithm in the figure. The NDE filter performs better than the NASRI filter for the noise densities 10%, 20%, 30%, 50%, 60%, 70%, 80%, 90% and 100%. From the figure,

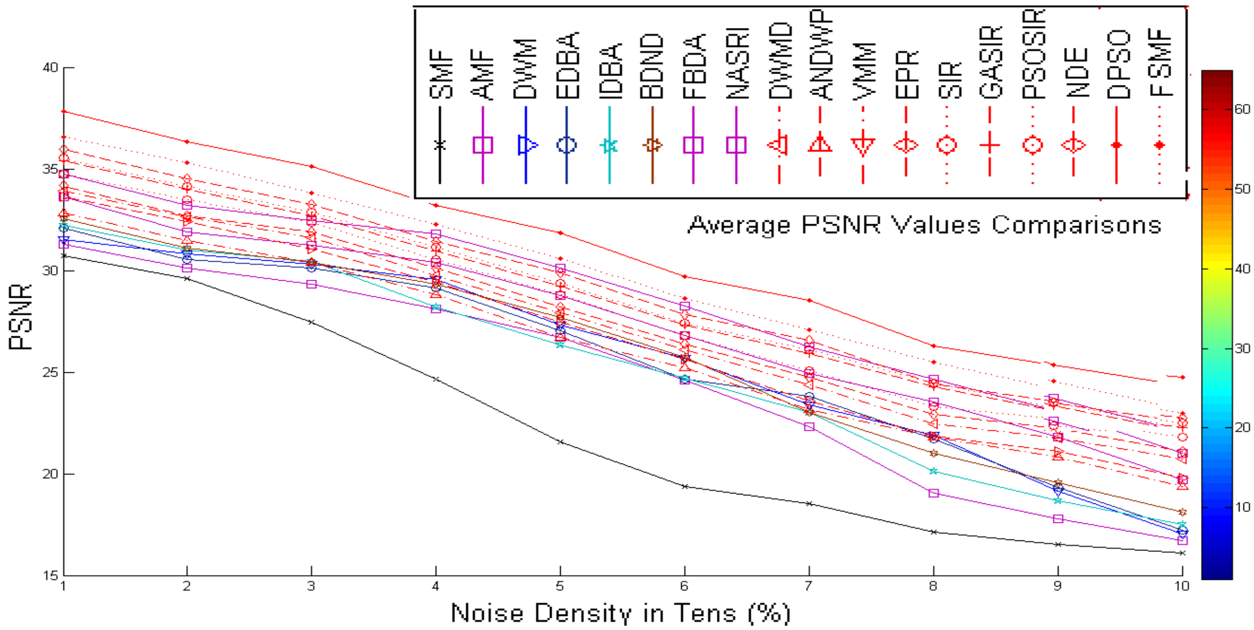



Figure 3: Graph of average PSNR values for *Lena*, *Cameraman*, *Liftingbody*, *Boat* and *Barbara* images for 10% to 100% RVNs by existing and **FSMF** filter

it can also be cleared that the **DPSO** algorithm has given much better restoration results in terms of IEF than the existing algorithms for the entire noise density. The algorithm also generated better IEF than other proposed filters such as DWMD, ANDWP, VMM, EPR, SIR, GASIR, PSOSIR and NDE. In Fig. 6, results are generated on the images corrupted by SPN. The *Average SSIM* values for all the algorithms are shown in this figure. From this figure, it is seen that for the entire noise density, the algorithm **DPSO** performs the best in terms of SSIM. The FSMF filter performs better than existing algorithms. The NASRI algorithm performs marginally better then the NDE filter. The SMF and AMF perform very poor where as DWM, EDBA and IDBA perform similarly. The BDND and FBDA have given similar SSIM values. In Fig. 7, results are generated on the images corrupted by RVN. The *Average SSIM* values are shown in this figure. From this figure, it can be shown that for the entire noise density, the **DPSO** algorithm performs excellent in terms of SSIM. The FBDA filter performs better than VMM filter. It can be cleared from the figure that the **DPSO** algorithm obtained much better restoration results than the existing algorithms for the entire noise density. The time required for execution of the proposed algorithms along with some existing algorithms for restoration of the five images having noise density of 50% using SPN and RVN are shown in Fig. 8 and Fig. 9 respectively. These values are given in terms of seconds. In case of SPN, the execution time for the standard median filter is very low for all the images used. The DWM filter performs excellent in terms of execution

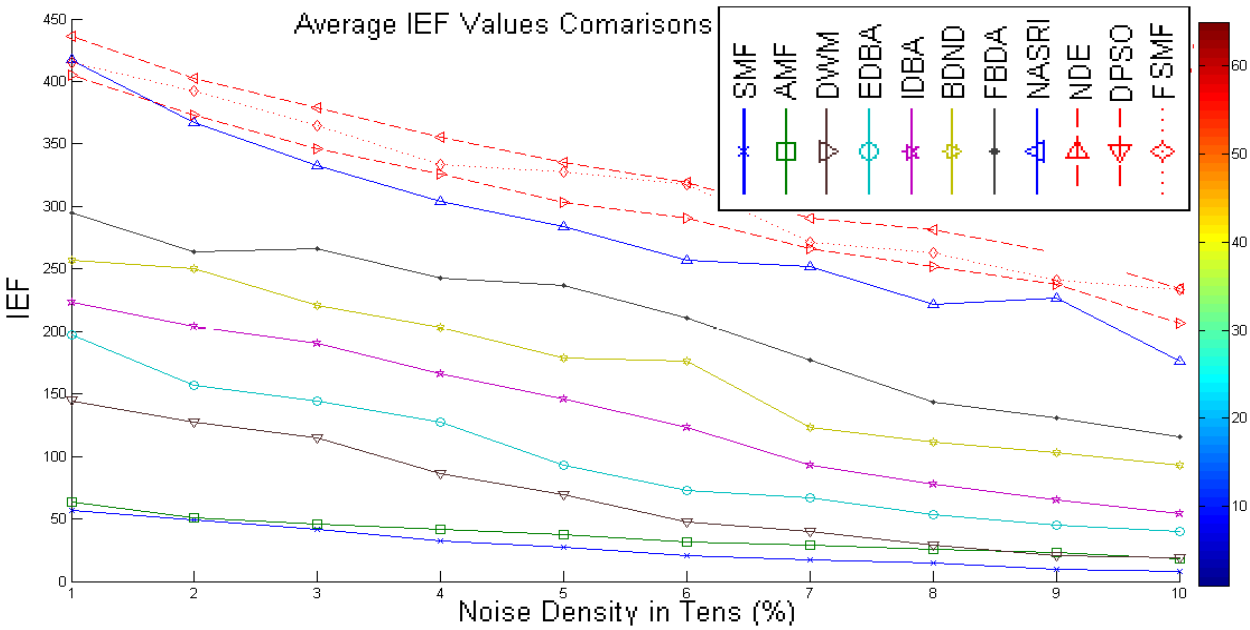



Figure 4: Graph of average IEF values for *Lena*, *Cameraman*, *Liftingbody*, *Boat* and *Barbara* images for 10% to 100% SPNs by existing and **FSMF** filter

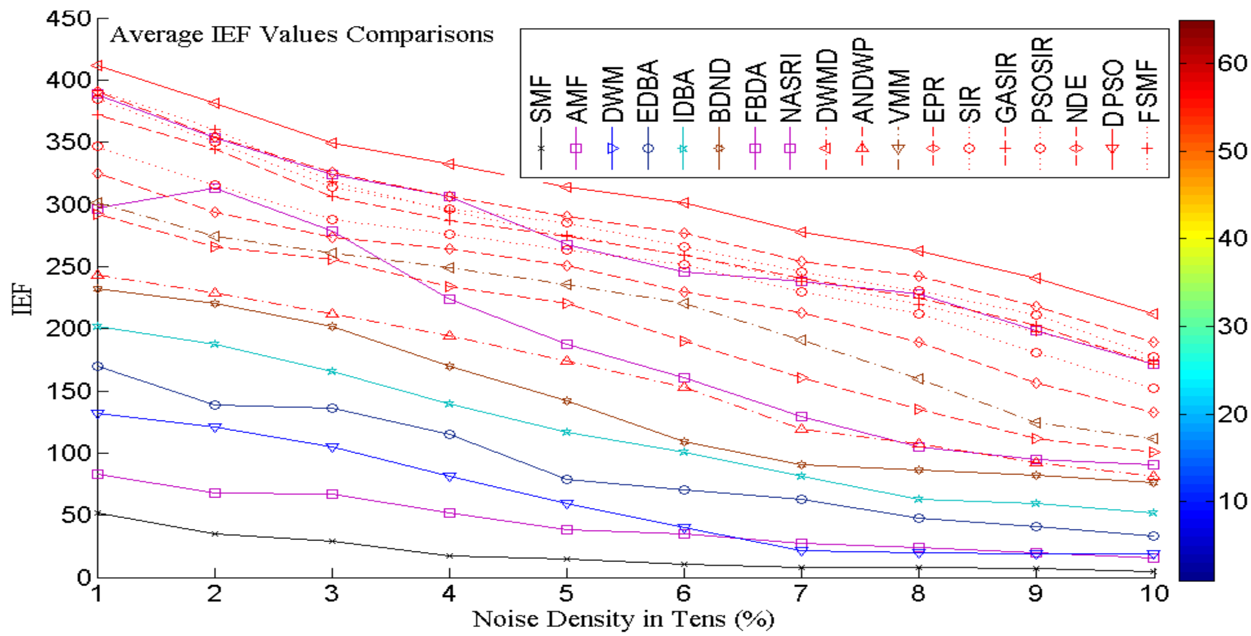



Figure 5: Graph of average IEF values for *Lena*, *Cameraman*, *Liftingbody*, *Boat* and *Barbara* images for 10% to 100% RVNs by existing and **FSMF** filter

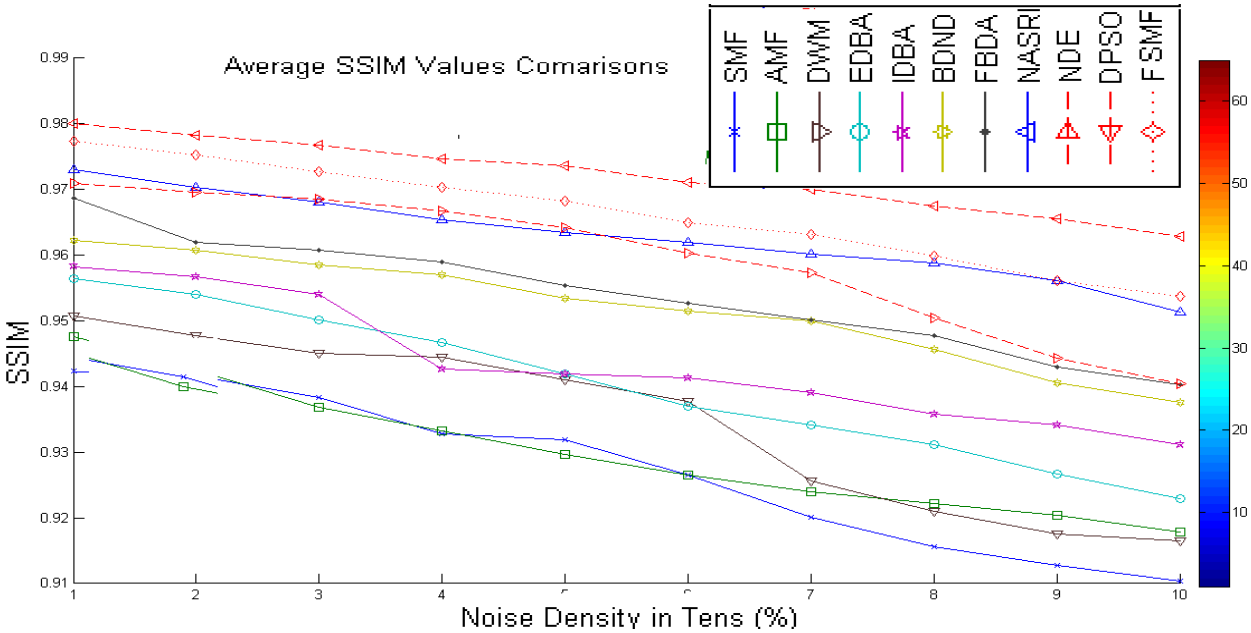



Figure 6: Graph of average SSIM values for *Lena*, *Cameraman*, *Liftingbody*, *Boat* and *Barbara* images for 10% to 100% RVNs by existing and **FSMF** filter

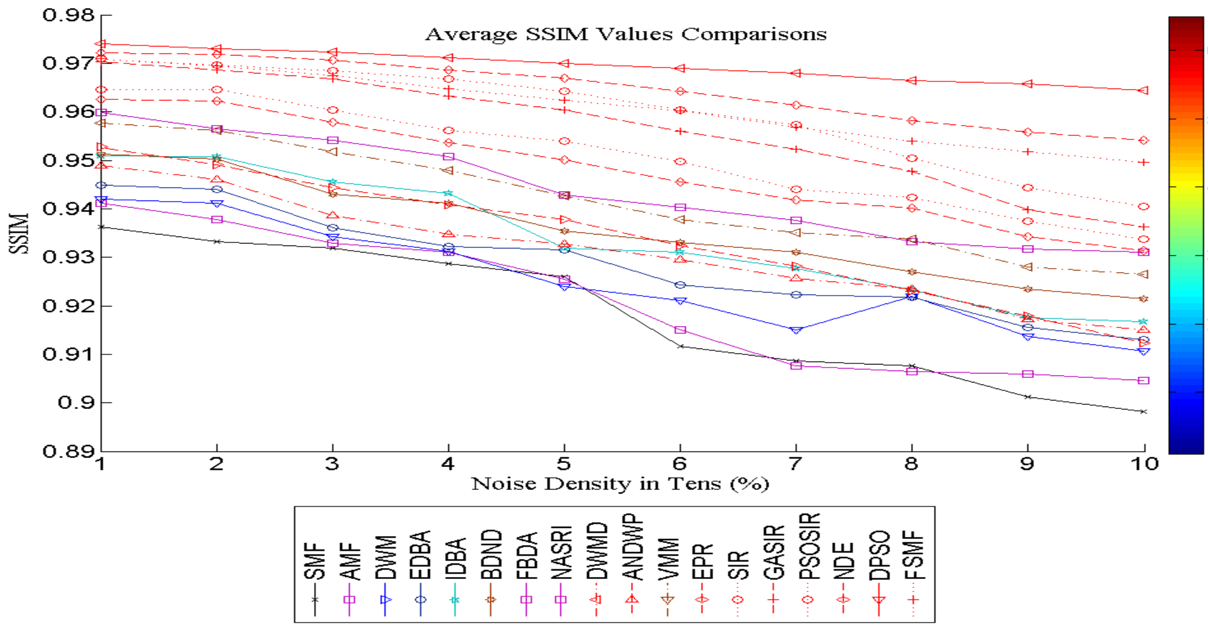



Figure 7: Graph of average SSIM values for *Lena*, *Cameraman*, *Liftingbody*, *Boat* and *Barbara* images for 10% to 100% RVNs by existing and **FSMF** filter

time. The EDBA takes more execution time than existing algorithms. Among the proposed algorithms, the FSMF filter needs less amount of time than the others. The NDE and DPSO require much larger times than all other algorithms. The proposed FSMF operator performs significantly better than the existing operators due to small window size and single time iteration used for the noise detection and filtering operations. For the RVN, the SMF and DWM filters perform excellent compared to other existing algorithms. The FBDA also requires less amount of time compared to other algorithms. Among the proposed algorithms, the DWMD, ANDWP, VMM and EPR require less amount of time. The PSOSIR defeats the GASIR algorithm, however they require more time than the SIR filter. The NDE requires maximum time for execution. The DPSO takes much more time than the others. The FSMF filter requires very less time compared to DPSO.

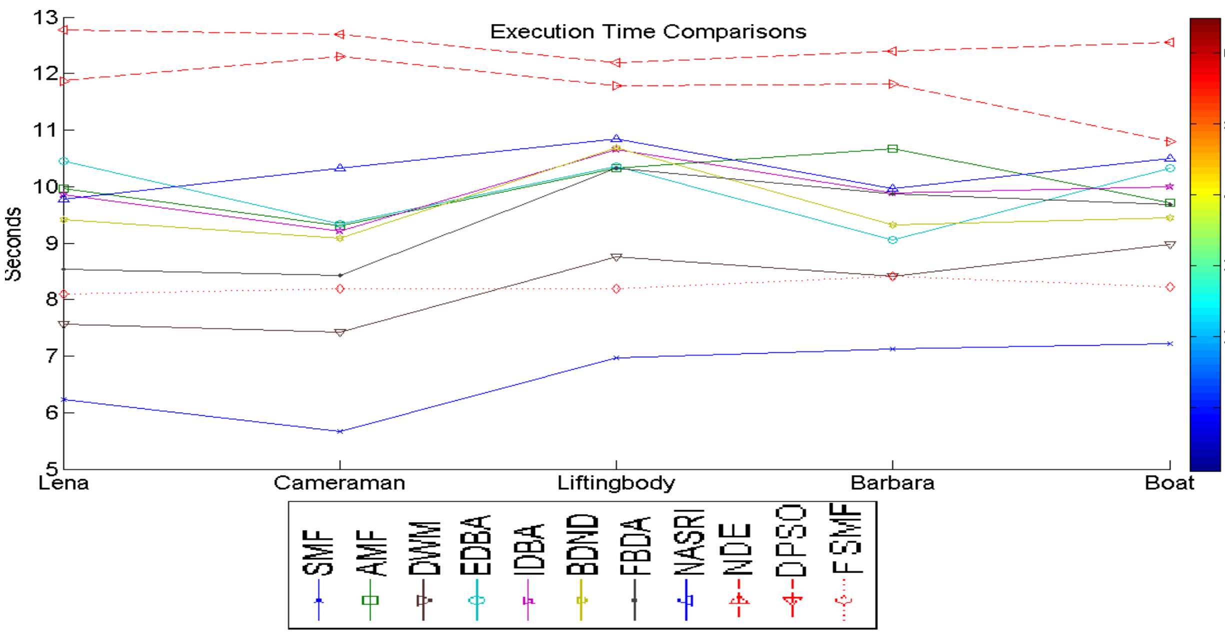



Figure 8: Comparisons of execution time (secs) for *Lena*, *Cameraman*, *Liftingbody*, *Boat* and *Barbara* images having 50% SPN

Results obtained using the proposed GA based BayesShrink has been compared with three existing filters on the Gaussian and Poisson noises in the wavelet domain. Fig. 10 shows the comparative restoration results in terms of PSNR (dB) under the specified noise conditions. This figure shows that the proposed filter performs significantly better than the existing filters.

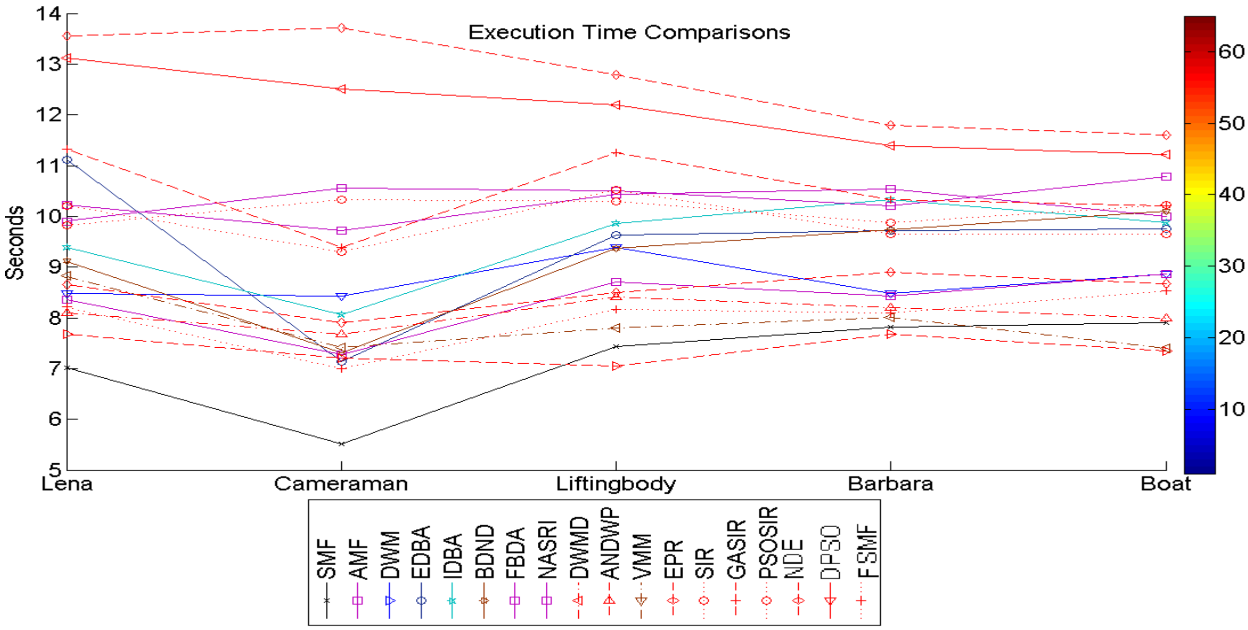



Figure 9: Comparisons of execution time (secs) for *Lena*, *Cameraman*, *Liftingbody*, *Boat* and *Barbara* images having 50% RVN

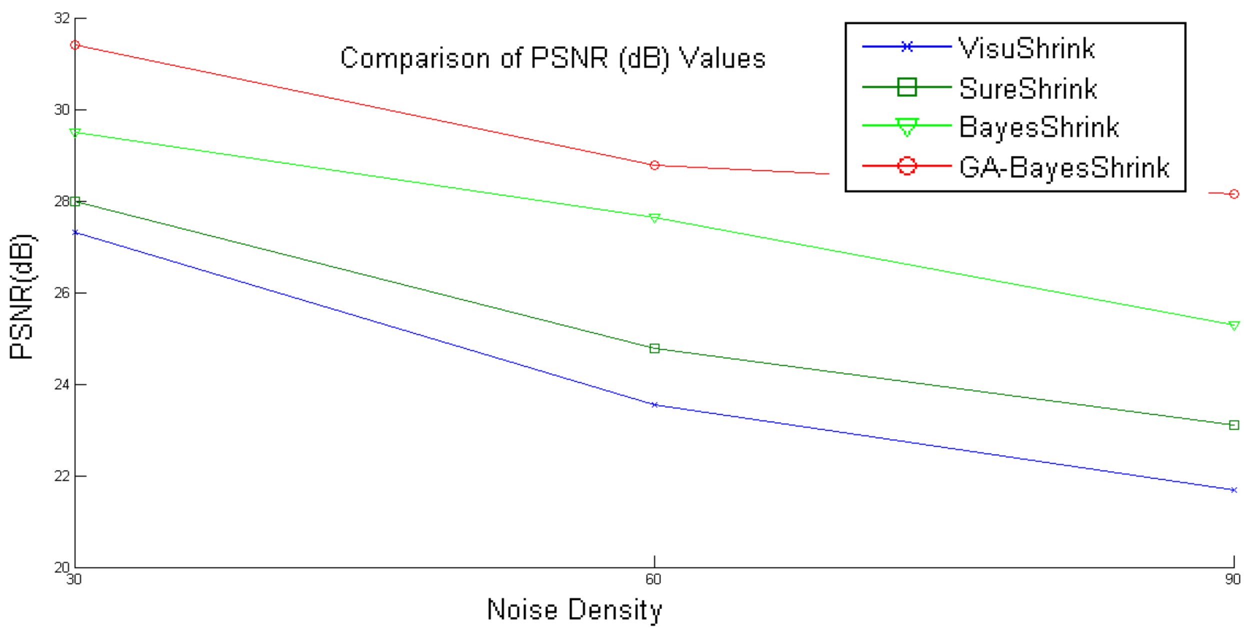



Figure 10: Graph representing comparison in *PSNR* for *Ultrasound* image corrupted by Gaussian and Poisson noises

## 0.4 Conclusive Discussions

Noise suppression, optimization and noise density estimation on the digital images have been proposed during the course of research. Salt and pepper noise and random valued noise in the digital images, and Gaussian and Poisson noises in the medical images are suppressed successfully. The other type of noise such as *Speckle noise* can be suppressed in the images. There is a scope of research to devise more noise suppression algorithms in the medical images. The other type of images such as Satellite images, X-ray images, computed tomography (CT) images, magnetic resonance imaging (MRI) images, nuclear medicine imaging, brain images and SAR images can be denoised. The Electrocardiogram (ECG) signal or heart sound and Electroencephalography (EEG) signal can also be investigated for denoising for better clinical diagnosis by the doctors. The frequency domain can be more utilized in the medical image denoising process. Another perspective is that new statistical measures can be developed to test the algorithmic performances and quality of the restored images.

# List of Publications

## Journals

1. Mukhopadhyay, S., Mandal, J.K.: A Fuzzy Switching Median Filter of Impulses in Digital Imagery (FSMF). Circuits, Systems and Signal Processing, 33(2), pp.1-24 (2014), Springer Science + Business Media New York. DOI 10.1007/s00034-014-9739-z

2. Mukhopadhyay, S., Mandal, J.K.: Denoising of digital images through PSO based pixel classification. Central European Journal of Computer Science 3(4), pp.158-172 (2013), Springer Vienna. DOI 10.2478/s13537-013-0111-3

3. Mandal J. K., Mukhopadhyay S.: A Novel Technique of Filtering High Random Valued Impulse Noise and Optimization through Genetic Algorithm (HRVINGA). AMSE Journal of Signal Processing and Pattern Recognition, France, Volume 55, Issue 2, No. 1-2, 2012, pp.37

4. Mandal J. K., Mukhopadhyay S.: Image Filtering using All Neighbor Directional Weighted Pixels: Optimization using Particle Swarm Optimization. In Signal and Image Processing: An International Journal (SIPIJ) Vol.2, No.4, pp. 187-200, December 2011, Academy and Industry Research Collaboration Center (AIRCC)

5. Mukhopadhyay, S., Mandal, J.K.: Image Denoising based on Sub-image Restoration through Threshold Optimization. **accepted** in International Journal of Computational Intelligence Studies (IJCIStudies), Inderscience Publishers, Geneva, Switzerland

## Book Chapters

6. Mandal J. K., Mukhopadhyay S.: Adaptive Median Filtering based on Unsupervised Classification of Pixels. (Handbook of Research on Computational Intelligence for Engineering, Science and Business, IGI Global, 701 E. Chocolate Ave., Hershey, PA 17033, USA)

## International Conferences

7. Mandal J. K., Mukhopadhyay S.: A Novel Directional Weighted Minimum Deviation (DWMD) based Filter for Removal of Random-Valued Impulses in Digital Images. International Conference on Computing and Systems (ICCS 2010), pp. 214-220, Burdwan University, India, November 2010

8. Mandal J. K., Mukhopadhyay S.: A Novel Technique for Removal of Random Valued Impulse Noise using All Neighbor Directional Weighted Pixels (ANDWP). International Conference on Advances in Parallel, Distributed Computing: Communications in Computer and Information Science (CCIS), Springer, vol. 203, pp. 102-111, Tirunelveli, Tamil Nadu, India, September 2011

9. Mandal J. K., Mukhopadhyay S.: GA based Denoising of Impulses (GADI). 10th International Conference on Computer Information Systems and Industrial Management Applications (CISIM 2011), Springer CCIS, vol. 245, pp. 212-220, Calcutta University, India, December 2011

10. Mandal J. K., Mukhopadhyay S.: A Novel Technique for Removal of Random Valued Impulses using Variable Mask Median Filter (VMM). International Symposium on Electronic System Design (ISED 2011), IEEE Computer Society, pp. 302-306, December 2011, Kochi, India

11. Mandal J. K., Mukhopadhyay S.: Edge Preserving Restoration of Random Valued Impulse Noises in Digital Images (EPRRVIN). International Conference on Recent Trends in Information Systems (ReTIS-11), IEEE Calcutta Section, pp. 309-314, Jadavpur University, India

12. Mandal J. K., Mukhopadhyay S.: PSO based Edge Keeping Suppression of Impulses in Digital Imagery. Proceedings of the International Conference on Information Systems Design and Intelligent Applications 2012 (INDIA 2012), Visakhapatnam, India, January 2012: Springer AISC, vol.132, pp. 395-403

13. Mukhopadhyay, S., Mandal J. K.: Wavelet based Denoising of Medical Images using Sub-band Adaptive Thresholding through Genetic Algorithm. Procedia Technology, Elsevier Ltd., 10(0), pp.680-689 (2013). First International Conference on Computational Intelligence: Modeling Techniques and Applications (CIMTA), University of Kalyani, India, 2013

14. Mukhopadhyay, S., Mandal, P., Pal, T., Mandal J. K.: Image Clustering based on Different length Particle Swarm Optimization (DPSO), **accepted** In International Conference on Frontiers of Intelligent Computing: Theory and applications (FICTA) 2014, Springer AISC, Bhubaneswar, India

# Publication Indexing Database

*The list of publications are indexed/abstracted in the following Databases which are mentioned in the following table serially.*

| **Publication Serial No.** | **Database** |
|---|---|
| 1 | SCOPUS, INSPEC, ACM Digital Library, Gale, SCImago, Google Scholar etc., |
| 2 | DBLP, Zentralblatt Math, OCLC, Summon by ProQuest, Google Scholar etc., |
| 3 | SCOPUS, IEEE-INSPECT, Elsevier BV, Institute for Scientific Information etc., |
| 4 | DBLP, ProQuest, EBSCO, Scribd, Google Scholar etc., |
| 5 | Academic OneFile (Gale), ACM Digital Library, Expanded Academic ASAP (Gale), Inspec., |
| 6 | Thomson Reuters, SCOPUS, DBLP, Compendex, PsycINFO, INSPEC, Cabell etc., |
| 7 | DBLP, Google Scholar etc., |
| 8 | SCOPUS, SCImago etc., |
| 9 | SCOPUS, DBLP etc., |
| 10 | SCOPUS, SCImago etc., |
| 11 | SCOPUS, SCImago, DBLP etc., |
| 12 | SCOPUS, Google Scholar etc., |
| 13 | SCOPUS, INSPEC, Google Scholar, ACM Digital Library, Gale, SCImago etc., |
| 14 | ISI Proceedings, DBLP, Ulrich's, EI-Compendex, SCOPUS, Zentralblatt Math, MetaPress etc., |

Table 1: Indexing Database of Publications

# List of Presentations

## International Conferences

1. Mandal J. K., Mukhopadhyay S.: A Novel Directional Weighted Minimum Deviation (DWMD) based Filter for Removal of Random-Valued Impulses in Digital Images. International Conference on Computing and Systems (ICCS 2010), pp. 214-220, Burdwan University, India, November 2010

2. Mandal J. K., Mukhopadhyay S.: GA based Denoising of Impulses (GADI). 10th International Conference on Computer Information Systems and Industrial Management Applications (CISIM 2011), Springer CCIS, vol. 245, pp. 212-220, Calcutta University, India, December 2011

3. Mandal J. K., Mukhopadhyay S.: A Novel Technique for Removal of Random Valued Impulses using Variable Mask Median Filter (VMM). International Symposium on Electronic System Design (ISED 2011), IEEE Computer Society, pp. 302-306, December 2011, Kochi, India

4. Mandal J. K., Mukhopadhyay S.: Edge Preserving Restoration of Random Valued Impulse Noises in Digital Images (EPRRVIN). International Conference on Recent Trends in Information Systems (ReTIS-11), IEEE Calcutta Section, pp. 309-314, Jadavpur University, India

5. Mandal J. K., Mukhopadhyay S.: PSO based Edge Keeping Suppression of Impulses in Digital Imagery. Proceedings of the International Conference on Information Systems Design and Intelligent Applications 2012 (INDIA 2012), Visakhapatnam, India, January 2012: Springer AISC, vol.132, pp. 395-403

6. Mukhopadhyay, S., Mandal J. K.: Wavelet based Denoising of Medical Images using Sub-band Adaptive Thresholding through Genetic Algorithm. Procedia Technology, Elsevier Ltd., 10(0), pp.680-689 (2013). First International Conference on Computational Intelligence: Modeling Techniques and Applications (CIMTA), University of Kalyani, India, 2013