HIGH DENSITY IMPULSE NOISE REMOVAL USING MODIFIED PROBABILISTIC DECISION BASED TRIMMED MEDIAN FILTER.

A Project report submitted in partial fulfilment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

ELECTRONICS AND COMMUNICATION ENGINEERING

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ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY AND SCIENCES
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(Permanently Affiliated to AU, Approved by AICTE and Accredited by NBA & NAAC)

Sangivalasa, Bheemunipatnam mandal, Visakhapatnam Dist.(A.P) 2021-2022

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CERTIFICATE

This is to certify that the project report entitled **"HIGH DENSITY IMPULSE NOISE REMOVAL USING MODIFIED PROBABILISTIC DECISION BASED TRIMMED MEDIAN FILTER"** submitted by **K.Tanuj(318126512028), G.Priyanka (318126512042), J.Sarayu(318126512022)** , **K.Rahul (318126512026)** in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology** in **Electronics & Communication Engineering** of Andhra University, Visakhapatnam is a record of bonafide work carried out under my guidance and supervision.

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ABSTRACT

In the present time of research in the field of image processing, a noise-free image is a noteworthy worry for separating significant data. This study focuses on the detection and removal of noisy pixels from an image contaminated by impulsive noise. A noise detection approach is developed to avoid the misinterpretation of noise-free pixel as noisy. In order to design the noise removal algorithm, a probabilistic decision-based improved trimmed median filter (PDITMF) algorithm is proposed which is intended to work out the conflict related to the even number of noise-free pixels in the trimmed median filter. It deploys two new estimation techniques for de-noising, namely, improved trimmed median filter (ITMF) and patch else ITMF (PEITMF) as per noise density. Trimmed median filter (TMF) works well in low-density noise while patch filter works well in high-density noise. The noise percentage is estimated and then for low-density noise, the trimmed median is utilized. For high-density noise, the patch else trimmed algorithm is incorporated. Switching concept is used in order to retain the NFPs.

At last, the noise detection approach is applied in the proposed PDITMF to build up a new technique called a probabilistic decision-based adaptive improved trimmed median filter (PDAITMF) algorithm. PDAITMF outperforms to all the above algorithms in context to peak signal-to-noise ratio as well as an image enhancement factor with the lower execution time at all noise densities.

CHAPTER – 1
INTRODUCTION

1.1 Project Objective:

The objective is to reduce the noise present in any digital image using any of the available filtering techniques and to evaluate the performance of each filtering technique in terms of the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR), elapsed time (ET), image enhancement factor (IEF) which are the four-error metrics used to compare image reconstruction quality.

1.2 Problem Statement:

In Digital Image Processing, removal of noise is a highly demanded area of research. Digital images are prone to a variety of types of noise. Noise is the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. Removal of noise is imperative before any kind of subsequent image processing tasks, such as edge detection or segmentation, because occurrence of this noise can severely damage the information or data embedded in the original image and makes them unusable. There are several ways that noise can be introduced into an image, depending on how the image is created. Images are often degraded by noises. Noise can occur during image capture, transmission etc. Noise removal is an important task in image processing. In general the results of the noise removal are well having a strong influence on the quality of the image processing technique. Several techniques for noise removal are well established in colour image processing. The nature of the noise removal problem depends on the type of the noise corrupting the image. In the field of image noise reduction several linear and nonlinear filtering methods have been proposed. Removal of noise is definitely an important area of research and there comes the need for filtering techniques for the removal of these noises. There are several basic filtering techniques in which choosing a particular filter with high efficiency depending on noise affected is difficult. Hence our project is concerned with comparative analysis of efficiency parameters of each filter for all noises considered. The most common type of noise can be broadly categorized by two noise generation models, namely, Gaussian noise and impulse noise. Generally, images are contaminated by impulsive noise, such as salt and pepper noise, Poisson noise and additive Gaussian noise at the time of its acquisition, transmission, and storage. Vibration may occur during imaging, which can introduce noise in an image. Among them, salt-and-pepper noise affect the most. Salt-and-pepper noise comes into play while dealing with any sort of images, such as remote sensing images, image related to agriculture, medical image such as brain MRI (magnetic resonance imaging) images, computed tomography scan images, ultrasound images, and X-ray images etc.

To overcome the above drawbacks, proposed PDAITMF to remove high-density impulse noise is proposed**.**

CHAPTER – 2

LITERATURE SURVEY

Kovac, B et.al [1] has proposed: "Mixed noise removal filter for multichannel images based on half-space deepest location":

The comparison of denoising results obtained with our algorithm and some state-of-the-art multi-channel denoising filtering methods has proven the effectiveness of our approach because of excellent PSNR values and visual quality of resulting images. Observed on a comprehensive corpus of benchmark images and wide range of noise powers, it is shown that HSDLF successfully preserves most of the edges and details from original images, and that there are no artefacts. More importantly, our filter takes into account the spectral correlation between channels in a multi-channel image. Also, it does not depend on either the nature or distribution of noise, or any specific digital image format, which means that it can be successfully implemented on lossy compressed image formats and other types of multi-channel noise. Future work based on this denoising technique should consider further adjustments and development of 'DEEPLOC' algorithm, especially in terms of choice of spatial directions which could improve 'HSDLF' accuracy and effectiveness.

Gellert, A., Brad, R et.al [2] has proposed: "Context-based prediction filtering of impulse noise images":

In this paper, we have proposed a new filtering method for impulse noise on greyscale images using context-based prediction. The CBPF replaces a pixel affected by salt-and-pepper noise with the pixel which occurred in its neighbourhood, determined by the search radius input parameter, with the highest frequency in the same context as the replaceable pixel. The frequencies of pixels occurring in a certain context are determined like in a Markov chain. Since our method is using context information, it can reconstruct details in the images affected by noise better than other methods. Due to the intrinsic behaviour, it could have a significant advantage on images containing textures. The limitation of the proposed method stands in the computational time required for denoising, which recommends it only for off-line processing of images.

Manjo, J.V et.al [3] has proposed: "Adaptive multiresolution non-local means filter for three dimensional magnetic resonance image denoising":

In this study, an adaptive multiresolution version of the blockwise non-local (NL)-means filter is presented for three-dimensional (3D) magnetic resonance (MR) images. On the basis of an adaptive soft wavelet coefficient mixing, the proposed filter implicitly adapts the amount of denoising according to the spatial and frequency information contained in the image. Two versions of the filter are described for Gaussian and Rician noise. Quantitative validation was carried out on BrainWeb datasets by using several quality metrics. The results show that the proposed multiresolution filter obtained competitive performance compared with recently proposed Rician NL-means filters. Finally, qualitative experiments on anatomical and diffusion-weighted MR images show that the proposed filter efficiently removes noise while preserving fine structures in classical and very noisy cases. The impact of the proposed denoising method on fibre tracking is also presented on a HARDI dataset.

Bhosale, N., Manza, R., Kale, K.V et.al [4] has proposed: "Analysis of effect of Gaussian, salt and pepper noise removal from noisy remote sensing images":

This paper attempts the pre-processing task of digital images are prone to a variety of noise. Noise is the result of errors in the image acquisition process that result in pixel values that do reflect the true intensities of the real scene due to that the process of removing noise from the original image is still a demanding problem for researchers. The prime focus of this paper is related to the preprocessing of a Remote sensing image before it can be used in applications. In order to achieve these de-noising of noisy remote sensing images. So, therefore we have used the filtering approach and analyze performance of each filter with respect to noise type. At last we have checked the image quality using standard quality measures. Hence, the filtering approach has been proved to be the best filter when the noisy remote sensing image is corrupted with Gaussian, Salt & Paper noises.

Ali, H.M et.al [5] has proposed: "Mri Medical Image Denoising By Fundamental Filters":

This paper investigated the performance of three different completely filtering methods tested with different noises on Magnetic Resonance Imaging (MRI) images. The Median filter is the most high performance method as compared to other filters mainly for Gaussian noise denoising. The Adaptive Median filter is the most outperformed method as compared to other filters mainly for Salt and Pepper noise de-noising.Through this work proved, the choice of filter depends upon the type and amount of noise present in an image. Also, the de-noising the MRI images performance depends on the type of noise and type of filtering techniques. The Median filter was better filter Magnetic Resonance Imaging images quality Gaussian noise. The Adaptive Median filter was better filter MRI image quality Salt and Pepper noise. The results showed that The Median filter has a better performance than other filters. The computation time and memory for the Median filter algorithm was increased than the Adaptive Wiener and Adaptive Median filters by400%.

Bashir, A., Mustafa, Z.A., Abdelhameid, I., et al [6] has proposed: "Detection of malaria parasites using digital image processing":

A system for detecting Plasmodium parasites was implemented.The images used in this work were collected from different sources, then the images were processed and certain features were extracted. These features were then used to detect the presents of the malaria parasite. In addition, a graphical user interface has been designed to facilitate the use of the system. A total of 1120 erythrocytes sub-images were used to train and test the performance of the system. The outputs of the system were compared to the results of expert microscopists. The results were promising and the sensitivity of the proposed method outperforms most of the other reported methods. The system recorded 99.68 % accuracy in detecting the presence of Plasmodium parasites. The neural network, which has been trained with the back propagation algorithm, improves the accuracy and performance of the system. Moreover, the automated computer based method introduced in this project is interactive; hence, it is faster and more accurate than manual process.

Gupta, S., Sunkaria, R.K et.al [7] has proposed: "Real-time salt and pepper noise removal from medical images using a modified weighted average filtering":

In this paper salt and pepper noise removal method is anticipated for medical images on the basis of weighted average pixels. The method is consisted two stages involve in salt and pepper noise suppression of real time medical images. These two stages are salt and pepper noise detection and image restoration. Better noise detection is done by using highly accurate salt and pepper noise detector and image is improved by weighted average filter. Simulation results using MATLAB software, performed on 256 x 194 MRI (Magnetic Resonance Imaging) brain image, 200 x 200 MRI knee image, 2017 Fourth International Conference on Image Information Processing (ICIIP) 242 350 x 250 mammogram image and 185 x 192 MRI head image are presented that the proposed approach is removed random value salt and pepper noise with high accuracy. The combination of noise detector with the modified weighted average filter are produced an improved value of peak signal to noise (PSNR) and good visual quality of image in comparison to the existing methods.This proposed method is quite suitable for real-time medical imaging system.

Gonzalez, R.C., Woods, R.E et.al [8] has proposed: "Digital image processing-Pearson Education":

This edition of Digital Image Processing is a major revision of the book. As in the 1977 and 1987 editions by Gonzalez and Wintz, and the 1992 and 2002 editions by Gonzalez and Woods, this fifth-generation edition was prepared with students and instructors in mind. The principal objectives of the book continue to be to provide an introduction to basic concepts and methodologies for digital image processing, and to develop a foundation that can be used as the basis for further study and research in this field. To achieve these objectives, we focused again on material that we believe is fundamental and whose scope of application is not limited to the solution of specialized problems. The mathematical complexity of the book remains at a level well within the grasp of college seniors and first-year graduate students who have introductory preparation in mathematical analysis, vectors, matrices, probability, statistics; linearsystems, and computer programming. The book Web site provides tutorials to support readers needing a review of this background material.One of the principal reasons this book has been the world leader in its field or more than 30 years is the level of attention we pay to the changing educational needs of our readers. The present edition is based on the most extensive survey we have ever conducted. The survey involved faculty, students, and independent readers of the book in 134 institutions from 32 countries

Yin, L., Yang, R., Gabbouj, M., et.al [9] has proposed: "Circuits and Systems Exposition Weighted Median Filters":

Finally, we would like to emphasize that although WM filters have some similarities with linear filters, WM filters cannot replace linear filters and vice versa. This is because WM filters cannot be designed in general to retain or restore some desired signal frequencies and reject others. This is connected with the fact that the weights in a WM filter are nonnegative. On the other hand, linear filters lead to poorer performance at signal edges and in the presence of non-Gaussian noise. Therefore, linear-weighted order statistic hybrid filters may be attractive in many cases. Although these adaptive hybrid filters have produced some interesting and promising results, more work needs to be done along this direction.

Hwang, H., Haddad, R et.al [10] has proposed: "Adaptive median filters: new algorithms and results":

Based on two types of image models corrupted by impulse noise, we propose two new algorithms for adaptive median filters. They have variable window size for removal of impulses while preserving sharpness. The first one, called the ranked-order based adaptive median filter (RAMF), is based on a test for the presence of impulses in the center pixel itself followed by a test for the presence of residual impulses in the median filter output. The second one, called the impulse size based adaptive median filter (SAMF), is based on the detection of the size of the impulse noise. It is shown that the RAMF is superior to the nonlinear mean L/sub p/ filter in removing positive and negative impulses while simultaneously preserving sharpness; the SAMF is superior to Lin's (1988) adaptive scheme because it is simpler with better performance in removing the high density impulsive noise as well as nonimpulsive noise and in preserving the fine details. Simulations on standard images confirm that these algorithms are superior to standard median filters.

Akkoul, S., Ledee, R., Leconge, R., et.al [11] has proposed: "A new adaptive switching median filter":

A new Adaptive Switching Median (ASWM) filter for removing impulse noise from corrupted images is presented. The originality of ASWM is that no a priori Threshold is needed as in the case of a classical Switching Median filter. Instead, Threshold is computed locally from image pixels intensity values in a sliding window. Results show that ASWM provides better performance in terms of PSNR and MAE than many other median filter variants for random-valued impulse noise. In addition it can preserve more image details in a high noise environment.

Faragallah, O.S., Ibrahem, H.M et.al [12] has proposed: "Adaptive switching weighted median filter framework for suppressing salt-and-pepper noise":

The paper presents an efficient approach for suppressing salt-and-pepper (S & P) noise under adaptive switching weighted median filter (ASWMF) framework. The ASWMF includes noise detection and noise removal stages. The proposed method first classifies a pixel into either "noise-free pixel" or "noise pixel" by checking noise candidate with the local mean value using noise detection stage. Then, the detected noisy pixels are replaced by their weighted median values using adaptive weighted median filter within a window size of 3 × 3 or 5 × 5. The proposed method is compared to several denoising schemes in terms of key performance indicators. Test results demonstrated superiority and efficiency over other methods in removing S & P noise up to percentage of 90%.

Zhang, P., Li, F et.al [13] has proposed: "A New Adaptive Weighted Mean Filter for Removing Salt-and-Pepper Noise":

In this letter, we have proposed an improved method based on AMF that can perform better in restoring image corrupted by high levels of SPN. It has much higher detection accuracy than AMF especially for high-level SPN. The computational time is similar for each level of SPN. Experimental tests show that our proposed AWMF method could perform better than many other existing filter.

Hsieh, M.H., Cheng, F.C., Shie, M.C., et.al [14] has proposed: "Fast and efficient median filter for removing 1–99% levels of salt-and-pepper noise in images":

This paper proposes a new median filter using prior information to capture natural pixels for restoration. In addition to being very efficient in logic execution, the proposed filter restores corrupted images with 1–99% levels of salt-and-pepper impulse noise to satisfactory ones. Without any iteration for noise detection, it intuitively and simply recognizes impulse noises, while keeping the others intact as no noises. Depending on different noise ratios at an image, two different sets of masked pixels are employed separately for the adoption of candidates for median finding. Furthermore, no limit to the size of mask windows assures that a proper median can be found. The simple logic of the proposed algorithm achieves significant milestones on the fidelity of a restored image. Moreover, the very fast execution speed of the proposed filter is very suitable for being applied to real-time processing. Relevant experimental results on subjective visualization and objective digital measure are reported to validate the robustness of the proposed filter

Khan, S., Lee, D.H et.al [15] has proposed: "An adaptive dynamically weighted median filter for impulse noise removal":

A new impulsive noise filter, adaptive dynamically weighted median filter (ADWMF), is proposed. A popular method for removing impulsive noise is a median filter whereas the weighted median filter and center weighted median filter were also investigated. ADWMF is based on weighted median filter. In ADWMF, instead of fixed weights, weightages of the filter are dynamically assigned with the results of noise detection. A simple and efficient noise detection method is also used to detect noise candidates and dynamically assign zero or small weights to the noise candidates in the window. This paper proposes an adaptive method which increases the window size according to the amounts of impulsive noise. Simulation results show that the AMWMF works better for both images with low and high density of impulsive noise than existing methods work.

Srinivasan, K.S., Ebenezer, D et.al [16] has proposed: "An adaptive dynamically weighted median filter for impulse noise removal":

A new decision-based algorithm is proposed for restoration of images that are highly corrupted by impulse noise. The new algorithm shows significantly better image quality than a standard median filter (SMF), adaptive median filters (AMF), a threshold decomposition filter (TDF), cascade, and recursive nonlinear filters. The proposed method, unlike other nonlinear filters, removes only corrupted pixel by the median value or by its neighboring pixel value. As a result of this, the proposed method removes the noise effectively even at noise level as high as 90% and preserves the edges without any loss up to 80% of noise level. The proposed algorithm (PA) is tested on different images and is found to produce better results in terms of the qualitative and quantitative measures of the image.

Esakkirajan, S., Verrakumar, T., Subramanyam, A.N., et.al [17] has proposed: "A new switching-based median filtering scheme and algorithm for removal of high-density salt and pepper noise in images":

A modified decision based unsymmetrical trimmed median filter algorithm for the restoration of gray scale, and color images that are highly corrupted by salt and pepper noise is proposed in this paper. The proposed algorithm replaces the noisy pixel by trimmed median value when other pixel values, 0's and 255's are present in the selected window and when all the pixel values are 0's and 255's then the noise pixel is replaced by mean value of all the elements present in the selected window. This proposed algorithm shows better results than the Standard Median Filter (MF), Decision Based Algorithm (DBA), Modified Decision Based Algorithm (MDBA), and Progressive Switched Median Filter (PSMF). The proposed algorithm is tested against different grayscale and color images and it gives better Peak Signal-to-Noise Ratio (PSNR) and Image Enhancement Factor (IEF).

Jayaraj, V., Ebenezer, D et.al [18] has proposed: "Removal of high-density salt & pepper noise through modified decision based unsymmetric trimmed median filter":

A new switching-based median filtering scheme for restoration of images that are highly corrupted by salt and pepper noise is proposed. An algorithm based on the scheme is developed. The new scheme introduces the concept of substitution of noisy pixels by linear prediction prior to estimation. A novel simplified linear predictor is developed for this purpose. The objective of the scheme and algorithm is the removal of high-density salt and pepper noise in images. The new algorithm shows significantly better image quality with good PSNR, reduced MSE, good edge preservation, and reduced streaking. The good performance is achieved with reduced computational complexity. A comparison of the performance is made with several existing algorithms in terms of visual and quantitative results. The performance of the proposed scheme and algorithm is demonstrated.

Aghajarian, M., Wright, C.H.G., Mclnroy, J.E et.al [19] has proposed: "A new method based on pixel density in salt and pepper noise removal":

The search for effective noise removal algorithms is still a real challenge in the field of image processing. An efficient image denoising method is proposed for images that are corrupted by salt-and-pepper noise. Salt-and-pepper noise takes either the minimum or maximum intensity, so the proposed method restores the image by processing the pixels whose values are either 0 or 255 (assuming an 8-bit/pixel image). For low levels of noise corruption (less than or equal to 50% noise density), the method employs the modified mean filter (MMF), while for heavy noise corruption, noisy pixels values are replaced by the weighted average of the MMF and the total variation of corrupted pixels, which is minimized using convex optimization. Two fuzzy systems are used to determine the weights for taking average The results show that the proposed scheme gives considerable noise suppression up to a noise density of 90%, while almost completely maintaining edges and fine details of the original image.

Erkan, U., Gokrem, L et.al [20] has proposed: "Salt-and-pepper noise removal using modified mean filter and total variation minimization":

The most repetitive noiseless pixel value within the window is set as the new pixel value. By using 18 test images, we give the results of peak signal-to-noise ratio (PSNR), structural similarity (SSIM), image enhancement factor (IEF), standard median filter (SMF), adaptive median filter (AMF), adaptive fuzzy filter (AFM), progressive switching median filter (PSMF), decision-based algorithm (DBA), modified decision-based unsymmetrical trimmed median filter (MDBUTMF), noise adaptive fuzzy switching median filter (NAFSM), and BPDF. The results show that BPDF produces better results than the above-mentioned methods at low and medium noise density.

Balasubramanian, G., Chilambuchelvan, A., Vijayan, S., et.al [21] has proposed: "Trimmed median filters for salt and pepper noise removal":

A new probabilistic decision based filter (PDBF) is presented to remove salt and pepper impulse noise in highly corrupted images. The filter employs two types of estimation techniques for denoising namely trimmed median (TM) and patch else trimmed median (PETM) which is our main contribution in this paper. Depending upon the estimated noise density, the filter utilizes either TM or PETM and hence enhanced outcome of denoising. Simulation results prove that the PDBF has outperformed recently proposed state-of-the-art filters in terms of peak signal to noise ratio (PSNR), structural similarity index (SSIM), image enhancement factor (IEF), mean absolute error (MAE) and visual representation at the noise densities (ND) as high as 95%.

Narayanan, S.A., Arumugam, G., Bijlani, P.K et.al [22] has proposed: "Trimmed median filters for salt and pepper noise removal":

With this paper we propose an iterative trimmed median filter and an adaptive window trimmed median filter for effective suppression of salt and pepper noise. The iterative trimmed median filter works in a way that, when a selected neighborhood window of a noise pixel is completely noisy, such pixels will be left unchanged in the current iteration and will be processed in the next iteration. The adaptive window trimmed median filter works in a way, when a selected neighborhood window of a noise pixel is completely noisy, the size of the neighborhood window is adaptively increased till an image pixel is found in the neighborhood. The visual quality of the denoised image using the proposed methods outperforms the Trimmed Median Filter (TMF) in terms of Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) values. At high noise densities, the proposed iterative filter outperforms the proposed adaptive window filter.

Beagum, S., Fareed, S., Khader, S.S et.al [23] has proposed: "Fast adaptive and selective mean filter for the removal of high-density salt and pepper noise":

A fast adaptive and selective mean filter is presented to remove salt and pepper noise effectively from images corrupted with higher noise densities. The algorithm achieves better results in terms of visual quality and in terms of peak signal-to-noise ratio, mean absolute error, mean structural similarity index measure, image enhancement factor, and edge preservation ratio than many existing state-of-the-art algorithms at all noise densities. Adaptive filters that use variable window size produce better restoration of salt and pepper noise at higher noise densities than filters that use fixed window size, but they consume more time. This makes them practically impossible to implement them in digital image acquisition devices. Hence, reducing the execution time of adaptive filters is vital. The proposed algorithm consumes around 90% less time for lower noise densities and 50% less time for higher noise densities than the adaptive weighted mean filter, one of the best available adaptive filters in the literature for high-density salt and pepper noise removal.

Samantaray, A.K., Kanungo, P., Mohanty, B et.al [24] has proposed: "Neighbourhood decision based impulse noise filter":

A novel impulse noise filter that preserves the image details and effectively suppresses high-density noise has been proposed in this work. The proposed filter works in two phases: (i) noise pixel detection phase and (ii) noise pixel restoration phase. In the detection phase, the impulse noise corrupted pixels are detected using a neighbourhood decision approach. In the second phase, the true values of corrupted pixels are restored using a first-order neighbourhood decision approach. Experiments are carried out with both grey scale and colour images of various resolutions, texture and structures. The proposed scheme has high peak-signal-to-noise ratio and better visual quality in comparison to the standard median filter, modified decision based unsymmetrical trimmed median filter and improved fast peer-group filter with a varying noise density from 10 to 90%.

Jaya Sree, P.S., Kumar, P., Siddavatam, R., et.al [25] has proposed: "Salt-and-pepper noise removal by adaptive median-based lifting filter using second-generation wavelets":

In this paper, we propose a novel adaptive median-based lifting filter for image de-noising which has been corrupted by homogeneous salt and pepper noise. The median-based lifting filter removes the noise of the input image by calculating the median of the neighboring significant pixels. The algorithm for image noise removal uses the lifting scheme of the second-generation wavelets in conjunction with the proposed adaptive median-based lifting filter. The experimental results demonstrate the efficiency of the proposed method. The proposed algorithm is compared with all the basic filters, and it is found that our method outperforms many other algorithms and it can remove salt and pepper noise with a noise level as high as 90%. The algorithm works exceedingly well for all levels of noise, as illustrated in terms of peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) measures.

Guo, D., Qu, X., Du, X., et.al [26] has proposed: "Salt and pepper noise removal with noise detection and a patch-based sparse representation":

Images may be corrupted by salt and pepper impulse noise due to noisy sensors or channel transmission errors. A denoising method by detecting noise candidates and enforcing image sparsity with a patch-based sparse representation is proposed. First, noise candidates are detected and an initial guide image is obtained via an adaptive median filtering; second, a patch-based sparse representation is learnt from this guide image; third, a weighted - regularization method is proposed to penalize the noise candidates heavier than the rest of pixels. An alternating direction minimization algorithm is derived to solve the regularization model. Experiments are conducted for 30%~90% impulse noise levels, and the simulation results demonstrate that the proposed method outperforms total variation and Wavelet in terms of preserving edges and structural similarity to the noise-free images.

Chen, J., Zhan, Y., Cao, H., et.al [27] has proposed: "Adaptive probability filter for removing salt and pepper noises":

To overcome the drawbacks of existing filters for salt and pepper noises, an adaptive probability filter is proposed. For an image, it detects salt and pepper noises based on the characteristic of minimum and maximum intensity values of the images, as well as the distribution of noise. If the noise-free intensities in neighbourhood repeat with a certain probability, the noise-free intensity with highest repeated frequency is used to remove noise based on the statistical significance; otherwise, the median of noise-free pixels in neighbourhood is used to remove noise. Experiments show that the proposed method is capable of detecting noise more accurately and perform much better than the existing distinguished filters in terms of peak-signal-tonoise ratio, image enhancement factor, and visual representation at all the noise densities.

Xing, Y., Xu, J., Tan, J., et.al [28] has proposed: "Deep CNN for removal of salt and pepper noise":

Image denoising is a common problem during image processing. Salt and pepper noise may contaminate an image by randomly converting some pixel values into 255 or 0. The traditional image denoising algorithm is based on filter design or interpolation algorithm. There exists no work using the convolutional neural network (CNN) to directly remove salt and pepper noise to the authors' knowledge. In this study, they utilise CNN with the multi-layer structure for the removal of salt and pepper noise, which contains padding, batch normalisation and rectified linear unit. In training, they divide images into three parts: training set, validation set and test set. Experimental results demonstrate that the architecture can effectively remove salt and pepper noise for the various noisy images. In addition, their model can remove high-density noise well due to the extensive local receptive fields of the deep neural networks. Finally, extensive experimental results show that their denoiser is effective for those images with a large number of interference pixels which may cause misjudgement. In a word, they generalise the application of CNN to salt and pepper noise removal and obtain competitive results.

CHAPTER – 3

NOISE DETECTION

3.1 Introduction

Noise 's the result of errors in the image acquisition process that results in pixel values that do not reflect the true intensities of the real scene.Noise reduction is the process of removing noise from a signal. Noise reduction techniques are conceptually very similar regardless of the signal being processed. however a priori knowledge of the characteristics of an expected depending signal can mean the implementations of these techniques vary greatly depending on the type of signal. The image captured by the sensor undergoes filtering by different smoothing filters and the resultant images. All recording devices both analog and digital, have traits which make them susceptible to noise. The fundamental problem of image processing is to reduce noise from a digital colour image. The two most common occurring types of noise are i) Impulse noise, ii) additive noise (e.g. Gaussian noise) and (iii) multiplicative noise iv) Poisson noise. Impulse noise is usually characterized by some portion of image pixels that are corrupted, leaving the remaining pixels unchanged .Examples of impulse noise are fixed-valued impulse noise and randomly valued impulse noise. We talk about additive noise when value from a certain distribution is added to each image pixel, for example, a Gaussian distribution. Multiplicative noise is generally more difficult to remove from images than additive noise because the intensity of the noise varies from the signal intensity (e.g., speckle noise).

3.2 Noise Definition

Noise represents unwanted information which deteriorates image quality. Noise is defined as a process (N) which affects the acquired image (F) and is not part of the scene (initial signal-S). Using the additive noise model, this process can be written as

$$F(i,j)=S(i,j)+N(i,j)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

The equation (1) represents the relation between noisy and original image where the original image ‘S’ at a pixel position (i,j) is effected by the noise ‘N’ at the same position (i, j) resulting in the final acquired image ‘F’ at (i, j).

Digital image noise may come from various sources. The acquisition process for digital images converts optical signals into electrical signals and then into digital signals and is one processes by which the noise is introduced in digital images. Each step in the conversion process experiences fluctuations, caused by natural phenomena, and each of these steps adds a random value to the resulting intensity of a given pixel. Image noise is the random variation of brightness or colour information in images produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detectos Image noise is generally regarded as an undesirable by-product of image capture. Although these unwanted fluctuations became known as "noise" by analogy with unwanted sound they are inaudible and such as dithering. Noise is random information. All images have certain amounts of noise in them. Some of it is not visible and in some images it is not visible. For instance when you take a digital photo in dark situations, you will notice that all the pixels have additional colour noises added due to the fact that the camera is created to give best results at bright light levels. Noise (n) may be modelled either by a histogram or a probability density function which is superimposed on the probability density function of the original image (s). In this project we deal with impulsive noise or salt and pepper noise.

Since anything that conveys information or broadcast a message in physical world between two observers is a signal. That includes speech or (human voice) or an image as a signal. Since when we speak, our voice is converted to a sound wave/signal and transformed with respect to the time to person we are speaking to. Not only this, but the way a digital camera works, as while acquiring an image from a digital camera involves transfer of a signal from one part of the system to the other.

3.3 Digital Image Formation

Since capturing an image from a camera is a physical process. The sunlight is used as a source of energy. A sensor array is used for the acquisition of the image. So when the sunlight falls upon the object, then the amount of light reflected by that object is sensed by the sensors, and a continuous voltage signal is generated by the amount of sensed data. In order to create a digital image , we need to convert this data into a digital form. This involves sampling and quantization. (They are discussed later on). The result of sampling and quantization results in an two dimensional array or matrix of numbers which are nothing but a digital image.
Digital images are formed by focusing rays of light or radiation on a photosensitive 2d sensor usually a Charge coupled device.

There are usually three optical filters in a typical digital camera. R-red, G-green and B-blue filters which are primary colors because they can be mixed in different proportions to form any color. There is a CCD sensor for each color channel, this allows the digital image to be reconstructed into a color form on a monitor.So the RGB format comes about because there are usually 3 CCD sensors in a camera. Each one corresponding to a particular color channel and while on a computer such images can be represented as a byte array and can be compressed or not.Each channel is encoded using 8bits thus an RGB pixel is 24bits long. Though RGB is not standard but ARGB is, the third channel A-alpha represents opacity levels and is usually not returned by a raw camera output. It is usually just added to RGB image format.

3.4 Noise Detection

It is considered henceforth, a salt-and-pepper noise is randomly distributed in an image having value `0' for pepper and `255' for salt with equal distribution which is illustrated in Fig. 1. Fig. 1a denotes an image of size 512 × 512 with a single intensity of 150 and Fig. 1b denotes its intensity histogram; Fig. 1c denotes an image of Fig.1 a with ND of 30% and Fig. 1d denotes the histogram of Fig. 1c. A total number of 39,274 pixels with an intensity value '0', 39,127 pixels with an intensity value '255' and 183,743 with an intensity value '150' are present. It is very much evident that while detection of salt-and-pepper noises on the basis of its analytical characteristics, intensity '255' and '0' may be wrongly picked up as noisy intensity. Therefore, all the pixels with intensities '255' and '0' should be carefully handled. Statistical characteristics of salt-and-pepper noises are as follows: • Salt-and-pepper noises are distributed randomly with equal probability in an image. • There exists a strong relationship within the NFP in a neighbourhood, so the NFP having intensities '255' or '0' are not isolated with its neighbouring pixels and are mostly to be closer to '255' or '0'. • It is of note that in a black neighbourhood corrupted by salt-and-pepper noises, the pepper noise cannot be identified as it fits in and are lost; so the entire pixels with an intensity value '0' are considered as NFP, while the pixels with an intensity value '255' are noisy. The same will be for white.

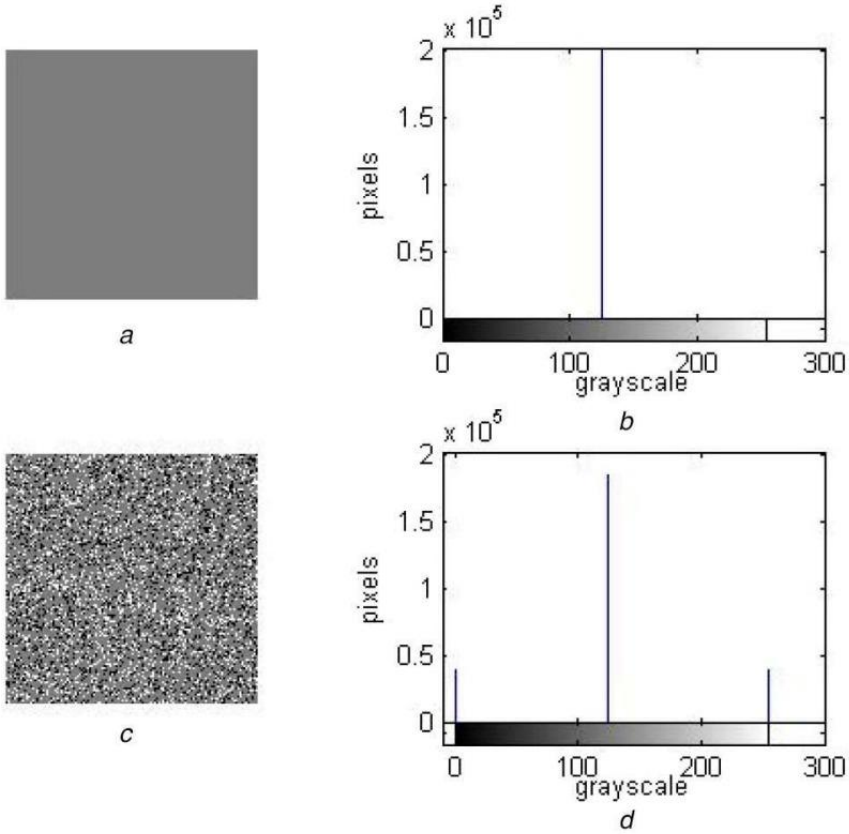


Figure 3.1 Properties of salt-and-pepper noise (a) Image with single intensity, (b) Histogram of ‘a’, (c) ND of 30% in image ‘a’, (d) Histogram of ‘c’

Through statistical analysis of pixels in an image, information of pixel being noisy or noise free is gathered and also relation of each pixel element with its neighbouring pixels is established. The pixels with intensity ‘255’ or ‘0’ which may or may not be noisy. It is to be detected by using the statistical information of the pixels as follows: an image 'Z', symbolised by Z(p) having pixel value 'p' ranges from 0 to 255. A neighbourhood Np(t) of a pixel value 'p' having size of $t \times t$ is considered. It is preferred to consider t=5, as t=3 is very small which may result in lacking of statistical importance, while $t \geq 7$ may result in lacking of correlation. k_i is symbolised as the number of pixels in Np(5) of intensity value 'i', k_i – the number of pixels in Np(5) of intensity value other than 'i'.

The proposed approach for detection of noise is explained as Assume Z(p) = 255 and $k_{255} >> k_0$, here $k_{255} > k_{255}$ – is set. From these conditions, it is inferred that its neighbourhood Np(5) is actually white or approximately white.

In such a case, pixel 'p' is then identified to be NFP; else, identified as noisy. Similarly, assume Z(p) = 0, if $k_0 >> k_{255}$, here $k_0 > k_0$ – is set, pixel 'p' is identified to be NFP, else identified as noisy. The 'S' denotes the logic matrix for noise identification which is assigned as zero matrix. The logic matrix 'S' is expressed as S = 1 for (Z(p) = 255 or 0) (1) 1S = 0 for (Z(p) = 255 or 0 and (k0 > k0 − or k255 > k255 −)) (2) where k0 denotes the number of pixels with intensity 0, k0– denotes the number of pixels other than intensity 0, k255 denotes the number of pixels with intensity 255 and k255– denotes the number of pixels other than intensity 255.

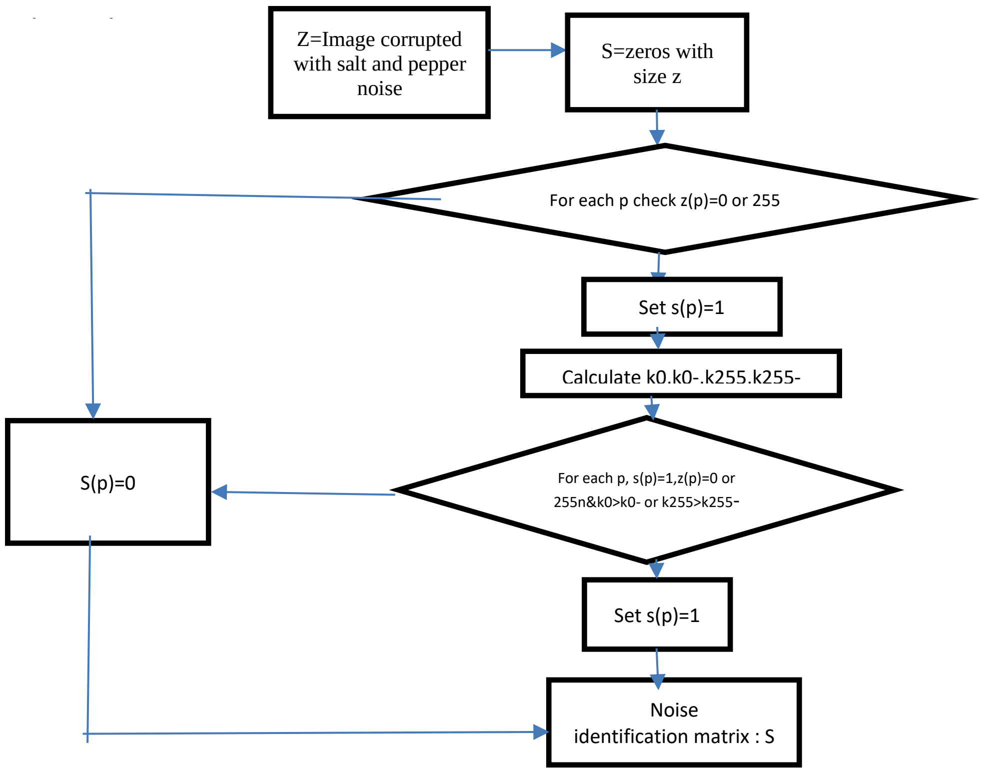


Figure 3.2 Noise Detection flowchart

3.5 Noise Removal - Trimmed Median Filter

The method trimming is a process of removing pixels that are not of importance before processing. If there is an occurrence of TMF, when the handling pixel is by all accounts noisy in the chosen window then pixel esteem with intensity 255 (salt) and 0 (pepper) are removed. The median of the NFP is then determined and is supplanted with the processing pixel. So far, many variations in the trimmed filter have been developed, but the problem with an even number of NFPs is not addressed till now. The UTMF lags while evaluating the image details for even number of NFPs. It basically calculates the average of two centre elements after sorting without mulling over whether the pixels are contiguous or not. The illustration of this technique is shown in Fig. 2a. A 3 × 3 window size has been considered as shown in Fig. 2a. Each of the 0 (pepper) and 255 (salt) is evacuated and afterward remaining components are orchestrated in rising request. The centre component is determined by averaging the two centre components. In this way, on the off chance that they are not adjoining one another, at that point it prompts some likelihood of obscuring in the image. In most of the cases, the processing pixel is supplanted by pixel that may not be the information of the respective window taken into account.

120	180	0
255	255	180
110	255	255

Patch median =180

110	180	0
120	255	180
255	255	255

Trimmed Median = Median of (110,120,180,180)
=(120+180) / 2 =150

0	110	180
120	180	255
255	255	255

Improved Trimmed Median = Compare (120,180)
As processing pixel = 255
So, pixel 180 will be ITM

Figure 3.3 Illustration of patch median, trimmed median, and proposed improved trimmed median

CHAPTER – 4

PROPOSED ALGORITHMS

4.1 Introduction

An image may be defined as a two dimensional function, f(x, y) and it is formulated as I = f(x, y) where x and y are spatial coordinates and I is the intensity or gray value at that point. When spatial coordinates and amplitude values are all finite, discrete quantities, then the image is called digital image. When a digital image is processed for receiving and analyzing visual information by digital computer, it is called as digital image processing . A digital image is composed of a finite number of elements. These elements have a particular location and value, which is most widely known as pixel. The other terms used for the pixel are picture element, image element and pixels. The digital image is represented by a single 2- dimensional integer array for a gray scale image and a series of three 2- dimensional arrays for each color bands. Image restoration means to retrieve the clean image from the degraded version of the image by removing the unwanted noise. Noise present in the image can be of additive or multiplicative type depending upon how the image is formed. Impulse noise is one of the additive types of noise present in the image during signal acquisition stage or due to the bit error in the transmission. There are two types of impulse noise found in the image, they are random value impulse noise and fixed value impulse noise (which is known as Salt and Pepper noise). In salt and pepper noise the corrupted pixels take the maximum (i.e. 255) value or the minimum (i.e. 0) value which leads to white and black spots in the image. These noises in any form should be removed from the image before further processing. In this paper we have proposed an efficient algorithm for the removal of salt & pepper noise from the image.

Many algorithms have been proposed for the removal of salt and pepper noise from the image over the past two decades. One of the most important issues in the image restoration is not only to remove noise but also to preserve the edge and texture details. To resolve this issue many good algorithms like Modified Decision Based Unsymmetric Median Filter (MDBUTMF) , Decision Based Partially Trimmed Global Mean Filter.

(DBPTGMF) and Modified Decision Based Partially Trimmed Global Mean Filter

(MDBPTGMF) are proposed. In these algorithms, a fixed 3X3 window is taken and when a corrupted pixel is found then it is replaced by either the mean, median or trimmed value of the pixels inside the window. As the noise density increases these algorithms fails to preserve the texture details of the image i.e. the originality is lost at high noise density.

An ITMF in probabilistic decision-based (PDITMF) approach is proposed. The algorithm settle the contention of an even number of NFP in TMF. The estimation techniques used to set up the proposed PDITMF algorithm are proposed improved trimmed filter (ITMF) and proposed patch else ITMF (PEITMF). So as to set up different connections, let NI be considered as the noisy image and Zd be the de-noised image.

4.2 Proposed ITMF

De-noising a picture if there should be an occurrence of an even number of NFPs is turning into a barrier for researchers. The proposed ITMF algorithm is useful to resolve this issue. This strategy is most appropriate for noises with low or medium densities. The strategy of the proposed ITMF is as follows:

Case 1. Odd valued NFP. For this situation, noisy pixels are removed and the remaining NFP are arranged. Median will be the centre element. For instance, if the ND is 40%, the likely number of noisy examples accessible in 3×3 window is 4, i.e. $0.4 \times 9 = 3.6 \equiv 4$, so NFP is $(9 - 4 = 5)$ which is an odd worth. Thus, subsequent to evacuating noisy pixels, the got NFPs are organized in expanding or diminishing request. The centre value is the median, which is utilised to supplant processing pixel.

Case 2. Even valued NFP. For this situation, a similar methodology is followed up to arranging. At that point a probabilistic estimation system is pursued which is clarified further. For instance, if the ND is 50%, the plausible number of noisy samples available in 3×3 window is 5, i.e, $0.5 \times 9 = 4.5 \equiv 5$, so NFP is $(9 - 5 = 4)$ which is an even value.

So, after removing noisy pixels, the acquired NFPs are orchestrated as in case 1. Now the two centre components might possibly be neighbouring one another. Here, a probabilistic methodology is taken to estimate the details of the image. The two center components are contrasted and on the off chance that the pixel will be handled is 255, at that point it is supplanted with the greater element and the other way around.

The proposed ITMF is experimented and compared with a number of recently reported established algorithms using some standard sample images. It is experimentally found that under the authors' knowledge, the ITMF outperforms the considered recently developed standard algorithms for low and medium NDs.

1.Select the window size of 3 x 3. Assume that the processing pixel is N1(J).
2. if 0 < NI(i,j)< 255 then
3. NI(i, j) is a noiseless pixel And its value is left unchanged.
4.end If
5. If NI(i, j)=0 or NI{ i, j}=255 then
6. N(i, j) is a noisy pixel, and the probabilities are
7. If the selected window contains all the pixels as 0 and 255 then
8. NI(i, j) is replaced by the mean of the selected window
9. else
10 Eliminate 0 and 255 from the selected window. Let the number or NFP be p1. Again two possibilities occur, they are,
11. if p1 is odd number then
12. Sort and find the median value.Replace it with NI(i,j).
13. else
14. Follow the below steps,
1. Sort the NFP
2.Compare (p1/2)th element and (pi /2 + 1)th element and store greater one in p2 and smaller one in p3
3. If NI(i, j) = 255, replace it with p2, else replace it with p3.
15: end if
16: End If
17: End if
18: Repeat the same procedure for all the pixels in the image.

Figure 4.1 ITMF algorithm

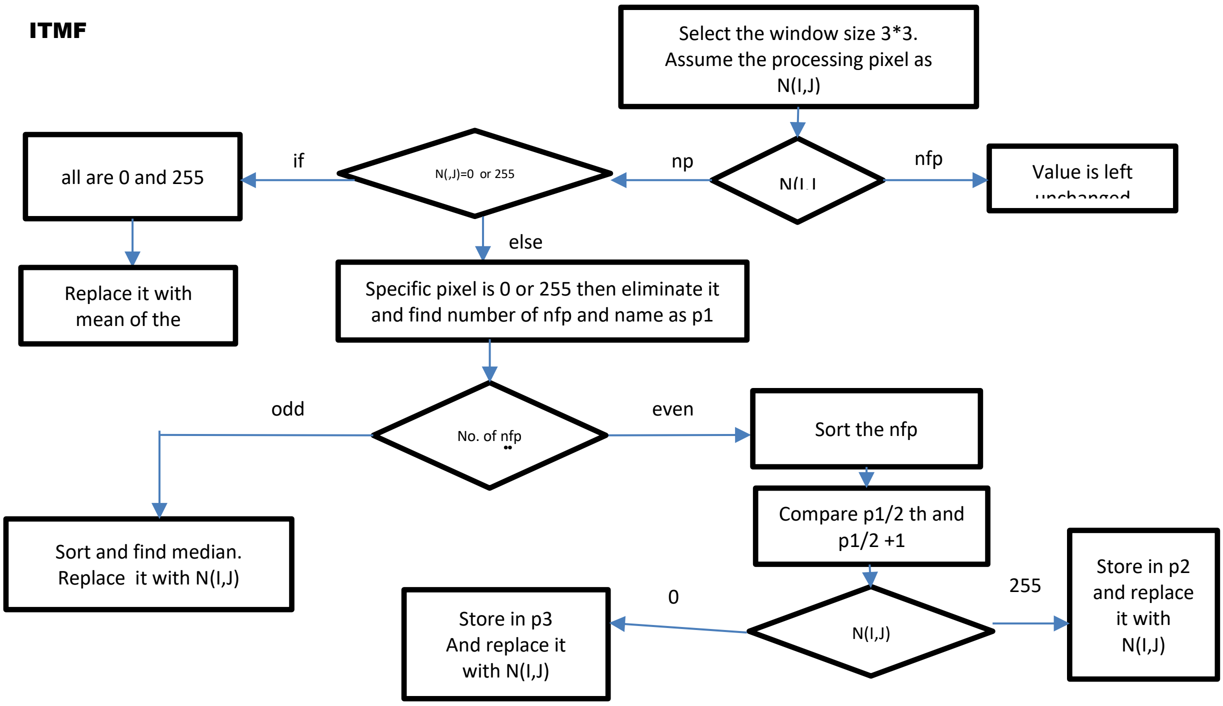


Figure 4.2 ITMF flowchart

4.3 Proposed PEITMF

In order to build up the proposed PDITMF algorithm, another system called patch else improved trimmed median filter (PEITMF) is proposed for high ND. The patch median (PM) is characterised for an odd estimated matrix, as a pixel element obtained at the centre of the matrix, after sorting the patch elements in rows and then columns or vice versa either in increasing or decreasing order. A single output is obtained by the patch median, whereas there is a probability that average output is obtained in trimmed median. In the proposed PEITMF, patch median is utilised with the proposed ITMF in the case of high ND. This concept is illustrated in Fig. 3.4.

Fig. 3.4 demonstrates that TMF in the greater part of the cases cannot appraise the fine subtleties of the image while the proposed ITMF performs magnificently. Along these lines, PM joined with the proposed ITMF is a decent probabilistic estimator of getting the original pixel information in a high ND.

Consider a 3 × 3 window size as shown in Fig. 3.4 PM is calculated as shown in Fig. 3.5. From the matrix, it is observed that the centre element is 180. So, the processing pixel gets replaced by pixel intensity of 180. As shown in Fig. 3.4, ITMF is calculated as 180, which is equal to the value of PM, while through trimmed median the intensity value is 150, which is not the information content of the matrix.

The algorithm experiments with sample images and a comparison is made between the proposed ITMF and the proposed PEITMF. The de-noising result in Figs. 3.3 and 4.4.1 shows that the proposed PEITMF performs more effectively compared to the proposed ITMF for ND> 60%.

```
 1: Find PM as the first estimate of the selected window.
 2: if obtained estimate is NFP then
 3:     consider this as the final intensity value.
 4: else
 5:     Find ITMF.
 6:     if obtained estimate is NFP then
 7:         consider this as the final intensity value.
 8:     else
 9:         increase size of the window and go to step 1
10:     end if
11:     Repeat the procedure till the NFP is obtained and stop.
12: end if
```

Figure 4.3 Proposed PEITMF algorithm

PEITMF Flowchart

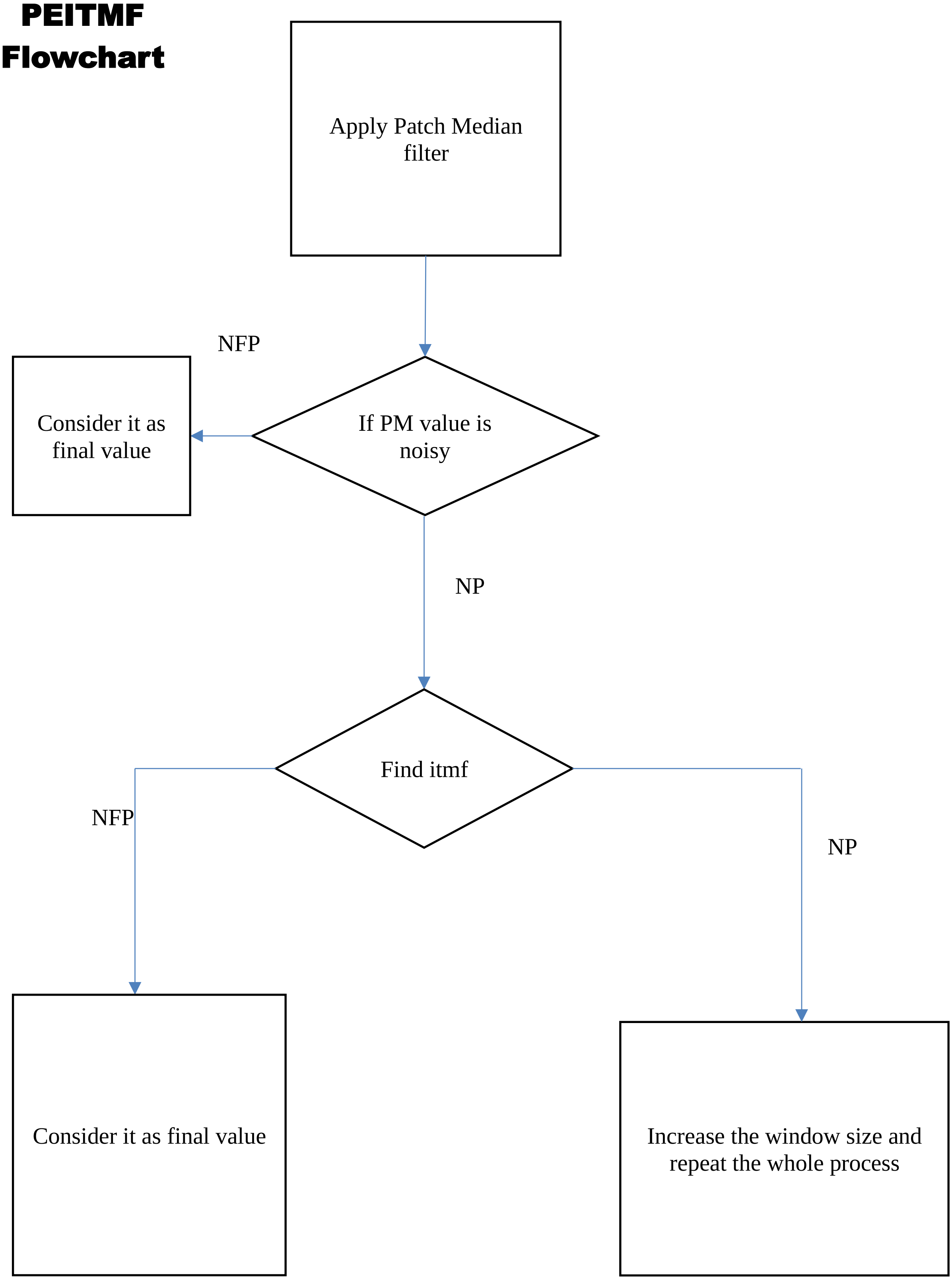


Figure 4.4 Proposed PEITMF flowchart

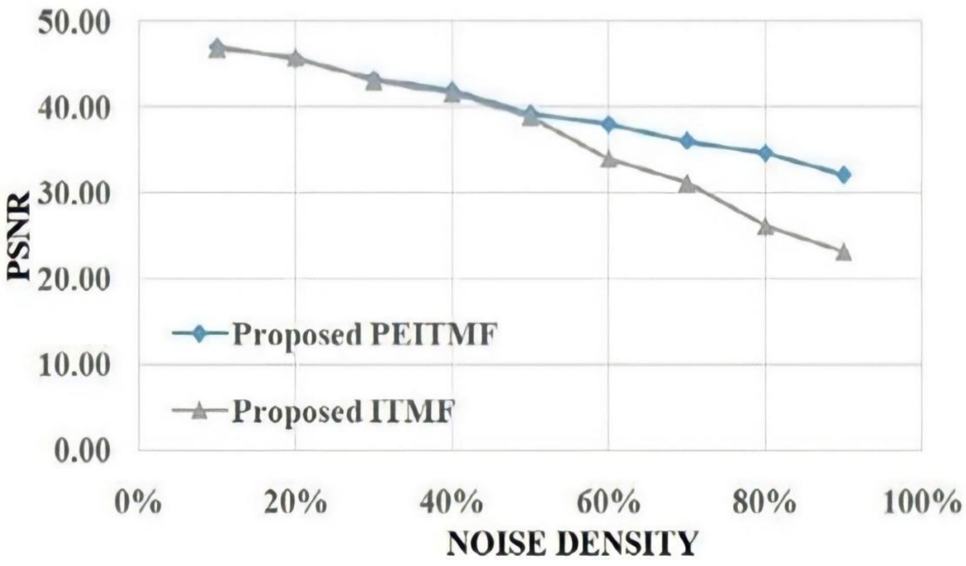


Figure 4.5 Proposed ITMF compared with considered algorithms making use of image pepper (sample image) in context to PSNR

4.4 Proposed PDITMF

To build up the proposed PDITMF algorithm, the proposed ITMF and PEITMF are implemented considering the certainties inferred in the above segments and the facts touched base which are as per the following:

(1) The proposed ITMF and proposed PEITMF performs excellently at low and medium NDs, i.e. ND < 60%.

(2) The proposed PEITMF performs sensibly all around contrasted with the proposed ITMF and gives some likelihood of showing signs of improvement estimation with ND ≥ 60%.

So as to determine a connection between the original image and noisy image, the pixel intensity of noisy image NI (i, j) at the pixel position (i, j) can be mathematically modelled as

NI (i, j) = Z(i,j) with the likelihood of (1-(ND/100))

NI(i, j)= 0 with the likelihood of (ND/200)

NI(i, j)= 255 with the likelihood of (ND/200)

The algorithm for the proposed PDITMF is set up as follows:

• For ND ≤ 50%, the proposed ITMF is utilised to dispose of the noisy pixels from the contaminated image.

• For ND > 50%, the proposed PEITMF is utilised to dispose of the noisy pixels from the contaminated image.

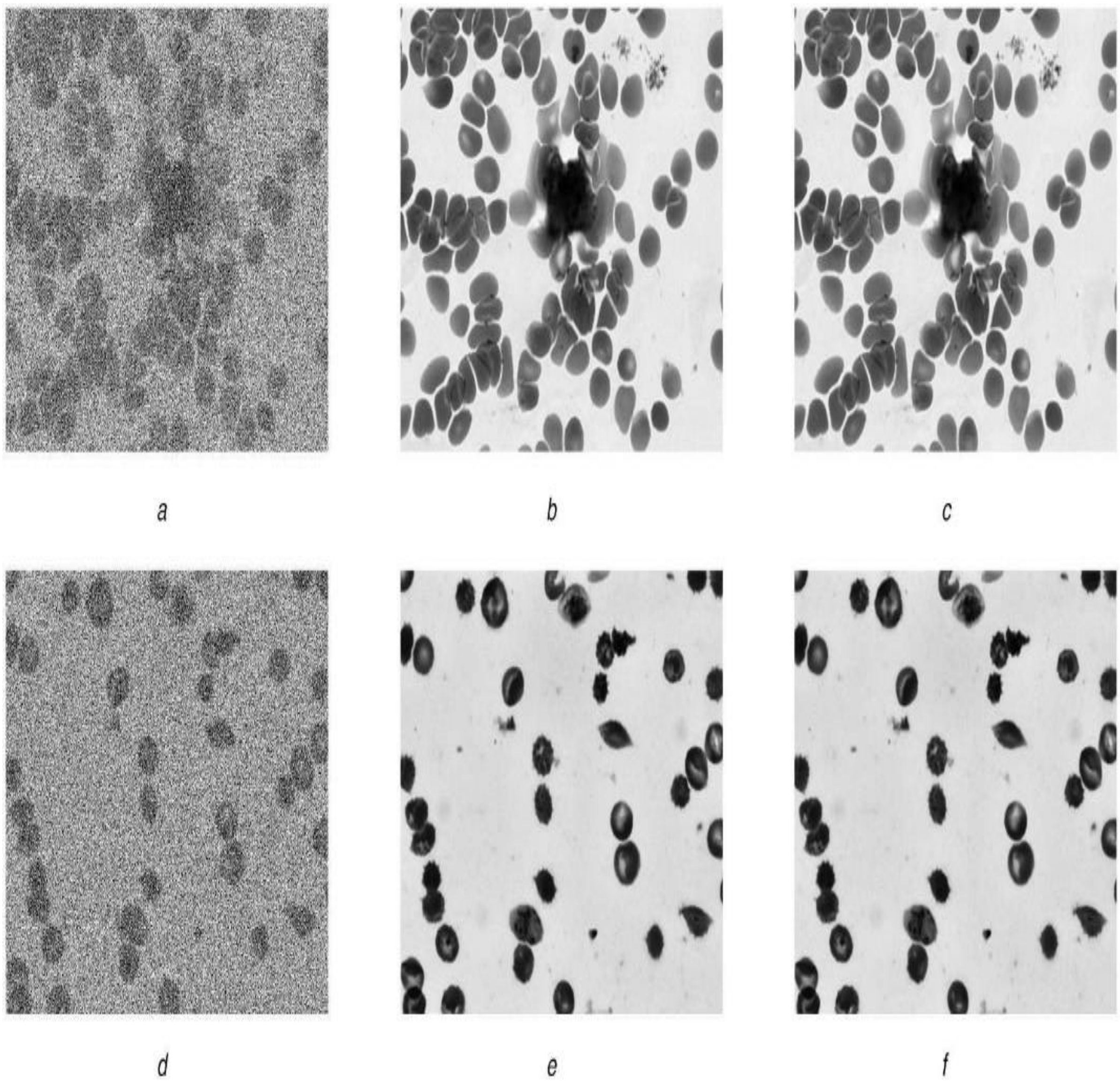


Figure 4.6 Visual Comparison between proposed ITMF and PEITMF (a), (d) Noisy 'image malaria_blood_smear1' and 'image malaria_blood_smear2' with ND = 70%, de-noising results obtained using, (b), (e) Proposed ITMF; and, (c), (f) Proposed PEITMF.

```
Evaluate noise density (ND).
if ND < 50 then
    set window condition
    if NI(i,j)=0 or 255 then
        find number of NFP p1 .
        if pi= 0 then
        increase window size till it is less than maximum allow-able window size.
        else
            Apply improved Trimmed Median Filter.
        end if
    end if
else
    Set window condition.
    if NI(i,j)= 0 or 255 then
        Apply Patch Median Filter in the selected window.
        if centre pixel = NFP then
            Place it as the new pixel.
        else
            if p1!= 0  then
                Apply the improved Trimmed Median Filter.
            else
                Increase window size till it is less than maximum allowable
            window size.
            end if
            If still noisy sample exist than the predictable sample is equal to last
            processed sample.
        end if
    end if
    Continue the procedure for entire pixels of the image and construct image using
    existing NFP    and estimated sample.
end if
```

Figure 4.7 Proposed PDITMF Algorithm.

PDITMF

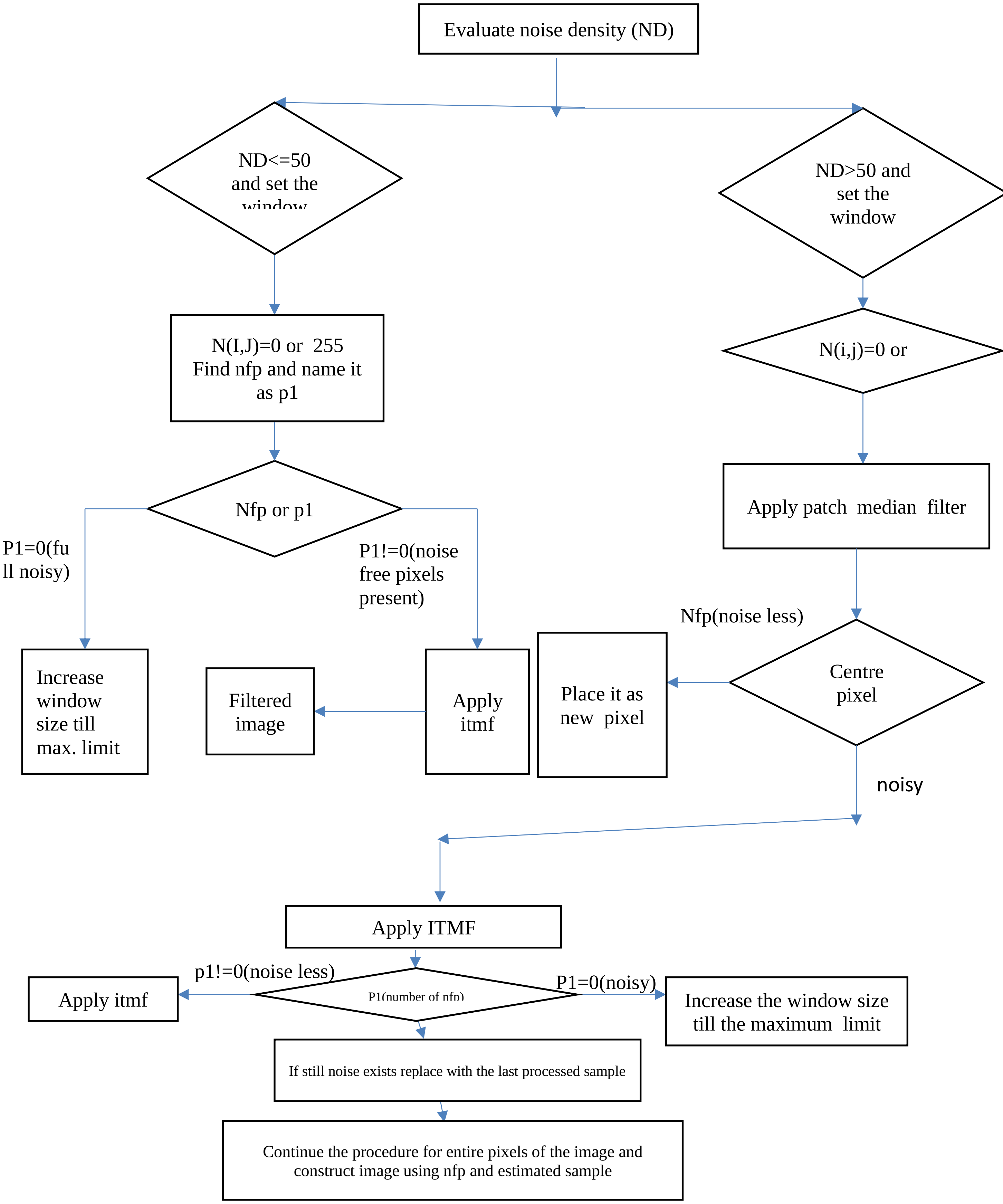


Figure 4.8 Proposed PDITMF flowchart

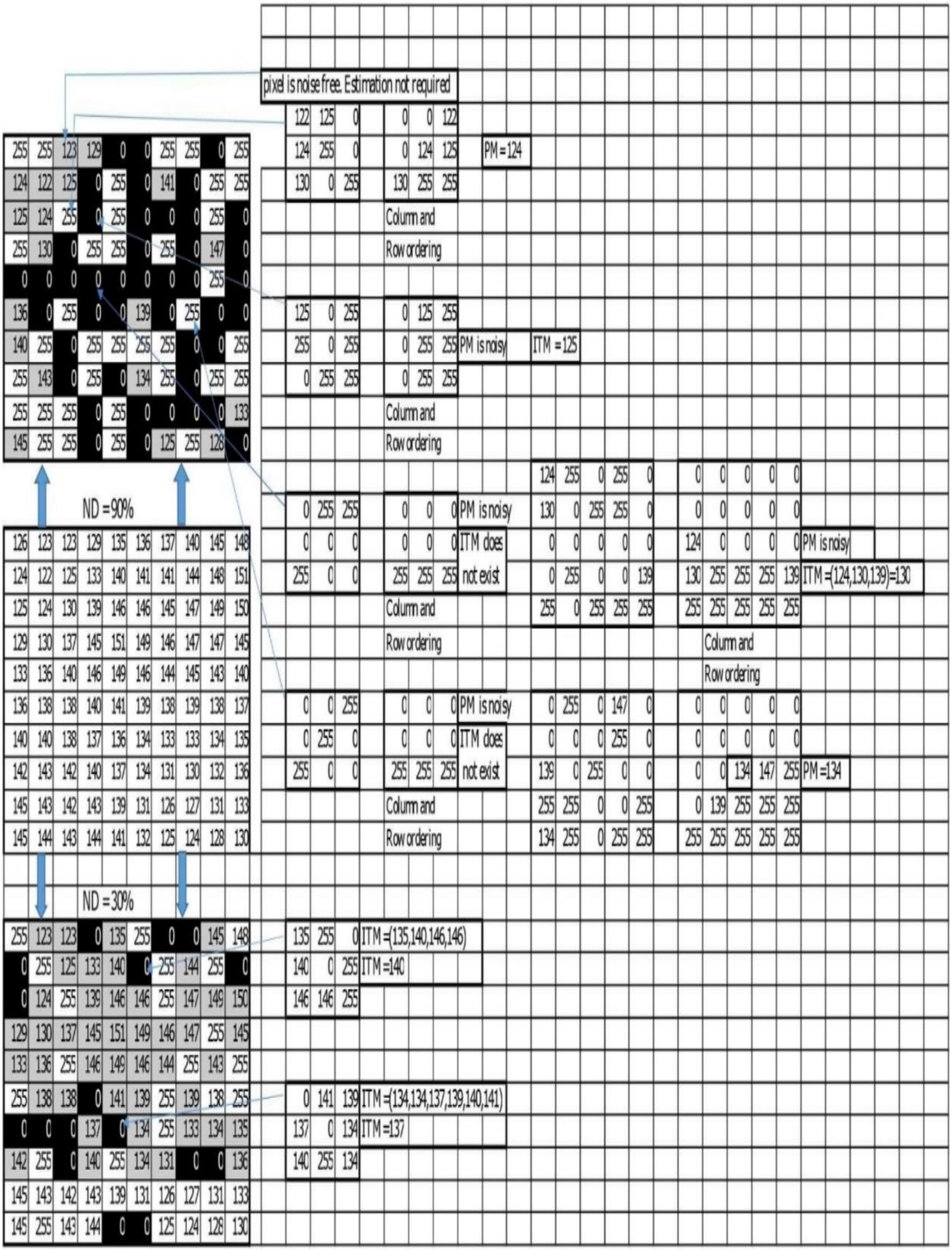


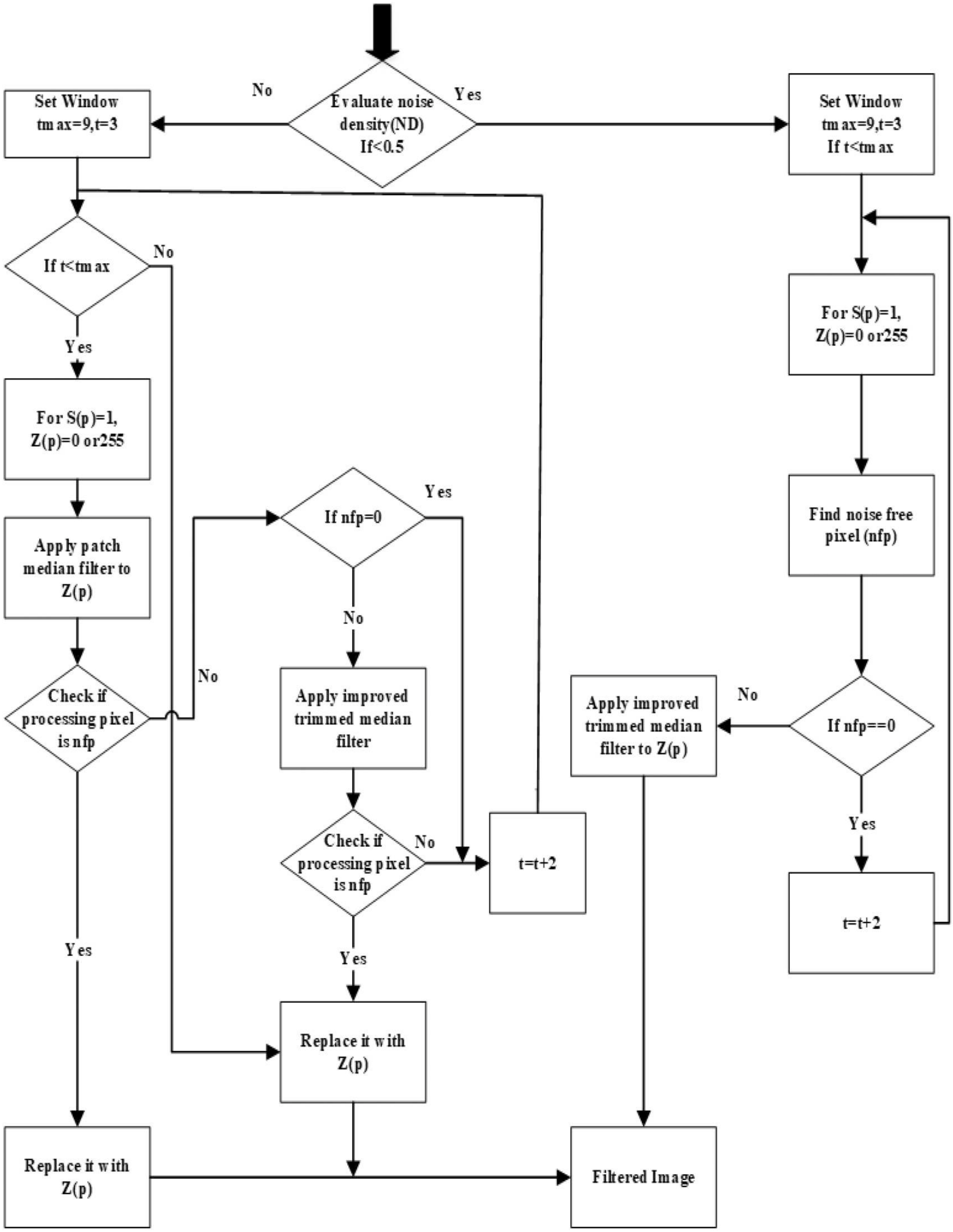
Figure 4.9 Exemplifications of the estimation employed in the proposed PDITMF

4.5 Proposed PDAITMF

In order to establish the proposed PDAITMF algorithm, ***S*** is symbolised as the logic matrix intended for noise identification initialised by ***S***=zeros [size(*Z*)]. Let *Np*(3) as neighbourhood of initial size and *Np*(*t*max) as neighbourhood of the maximum size. The optimal value for *t*max is verified as 9. Maintaining the computational complexity to a comparable level, its de-noising performance is better compared to other existing algorithms. The algorithm of the proposed PDAITMF is shown in Algorithm 4.5.1.

1: For each pixel p, if Z(p) = 0 or 255, set S(p)=1.
2: For each pixel p with S(p)=1, in its Np(t), if Z(p)=0 and kO>k0-, or Z(p)=255 and k255>k255-, reset S(p)=0.
3: For each pixel p with S(p)=1, in its Np(t), if Z(p)=0 and kO>kO-, or Z(p)=255 and k255>k255-, reset S(p)=0.
4: For S(p)=1 and if Z(p)=0 or 255, find NFP.
5: If NFP=0, increase Np(t) till it is less than maximum allowable window size.
6: Else apply improved Trimmed Median Filter to Z(p).
7: Set window condition. For S(p)=1 and if Z(p)=O or 255, apply Patch Median Filter to Z(p).
8: Check if Z(p) = NFP, replace it with Z(p).
9: Else check for NFP not equal to zero in Np(t),
10: If NFP = 0, apply the improved Trimmed Median Filter.
11: Else increase Np(t) till it is less than maximum allowable window size.
12: Goto step 7.
13: If still noisy sample exist than the estimated sample is same as last processed sample.
14: Continue the procedure for all the pixels in the image and construct image using existing NFP and estimated sample.

Figure 4.10 Proposed PDAITMF algorithm



(a)

Figure 4.11 Noise removal (PDAITMF) flow chart

CHAPTER 5
RESULTS

5.1 Simulation results and discussion

The proposed PDAITMF and the proposed PDITMF are investigated and compared against some of the newly reported algorithms like NAFSM-2010, MDBUTMF-2011, PDBF-2016, BPDF-2018 and APF-2018. The greyscale images are collected from authentic standard image websites named www.imageprocessingplace.com, www.data.broadinstitute.org and www.sipi.usc.edu. Images of Lena, lady, house, pepper, chest-Xray, brain-MRI, flower, Mandril and Malaria_blood_smear areselected for the experiments. All the images are of size 512 × 512. The experiments are conducted using MATLAB R2013b environment. The simulation is performed, investigated, tabulated and presented against some of the recently reported state-of-the-art, such as NAFSM-2010, MDBUTMF-2011, PDBF-2016, BPDF-2018, APF-2018 and proposed PDITMF.

5.2 Evaluation measures for validation

The proposed algorithm is evaluated and compared against the considered algorithms in terms of PSNR, IEF, ET, mean square error (MSE) and mean absolute error (MAE). The above mentioned parameters are defined as follows and The performance is considered better with the increase in the PSNR and IEF, while the MSE, MAE, and ET should be as low as possible. ET is calculated using Matlab command 'tic' and 'toc'.

MSE: Mean Square Error

MSE is nothing but the average error due to the total no. of pixels present in an image. A definition of MSE does not show that the noise removed image encounters additional number of errors rather it adverts to an additional well-known dissimilarity between the original and the noise removed image. This indicates that there is a critical noise reduction. The formula for the MSE calculation is given by Equation

$$\mathrm{MSE} = \frac{1}{mn}\sum_{\mathrm{i=0}}^{\mathrm{m}}\sum_{\mathrm{j=0}}^{\mathrm{n}}[\mathrm{I(i,\ j) - K(i,\ j)}]^2$$

Here, original image is represented as I(i,j) & K(i,j) is the corrupted image.

MAE: Mean Absolute Error

It is the Difference between original and enhanced image. As the name suggests, the mean absolute error is an average of the absolute errors , where is the prediction and the true value. Note that alternative formulations may include relative frequencies as weight factors. The mean absolute error used the same scale as the data being measured.

$$\mathrm{MAE} = \frac{\sum_{i,j}^{m,n} (Z_{i,j} - Z_{d_{i,j}})}{m \times n}$$

PSNR: Peak Signal to Noise Ratio

The PSNR is used to measure the quality among two images. In image filtering, PSNR can be evaluated between the original/input image and the recovered image. Here, MSE is used to define PSNR. For two-dimensional M x N monochrome images, the formula of PSNR is given in Equation

$$\mathrm{PSNR} = 10\log\left(\frac{\mathrm{MAX}_i^2}{\mathrm{MSE}}\right)$$

Where, the maximum value in an image can be represented by MAX. If 8 bits per samples are used to represent the pixel then MAX is 255. Higher the PSNR gives better quality.

IEF: Image Enhancement Factor

IEF is qualitative measure of the recovered images and it is termed as the proportion of the distinction of degraded image and input image to the variation of the recovered image and the original image.

$$IEF = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(x(i,j) - e(i,j))^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}(f(i,j) - e(i,j))^2}$$

Here, original image is represented as e(i,j) & f(i,j) is the corrupted image.

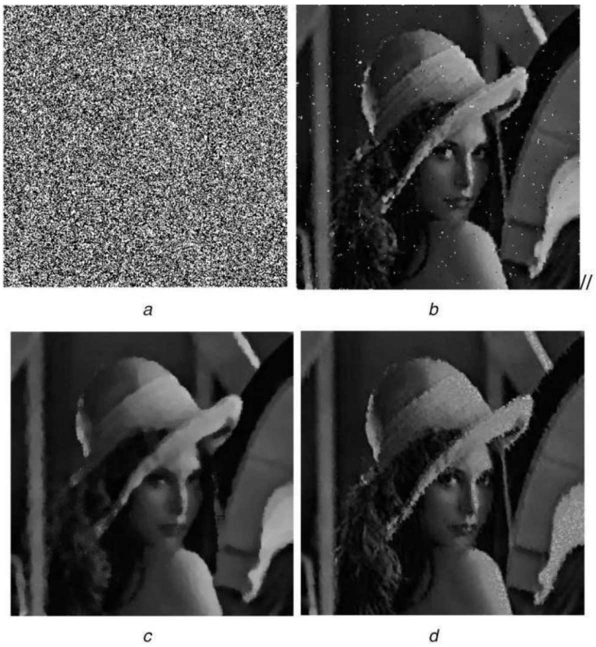


Figure 5.1 Comparison of PDAITMF in terms of visual appearance against considered algorithm with 90% ND using image Lena
(a) Noisy image, **(b)** NAFSM, **(c)** MDBUTMF and, **(d)** PDBF

Figure 5.2 Comparison of PDAITMF in terms of visual appearance against considered algorithm with 90% ND using image Lena
(a) BPDF, **(b)** APF, **(c)** PDITMF and, **(d)** PDAITMF

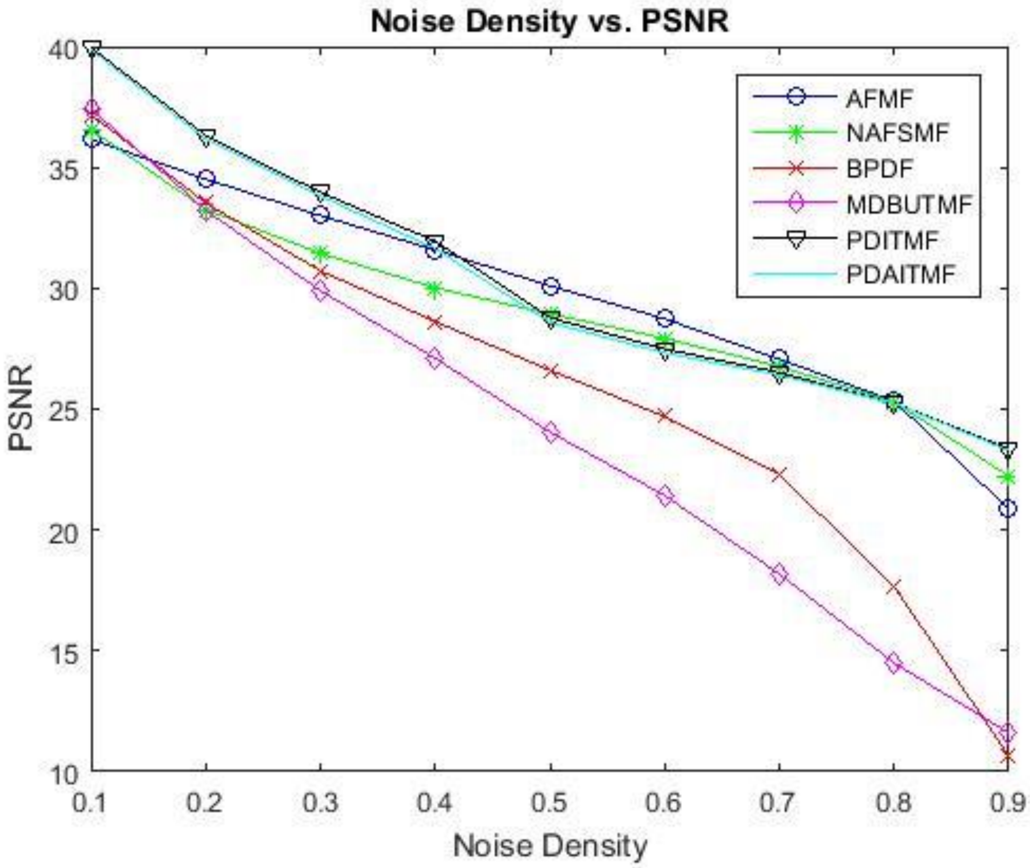


Figure 5.3 Noise density vs PSNR graph for different methods.

Table 5.1 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image lena in context to PSNR**.**

ND, %	AFMF	NAFSM	MDBUTMF	BPDF	Proposed PDITMF	Proposed PDAITMF
10	36.15	36.56	37.42	37.19	39.96	39.86
20	34.51	33.25	33.23	33.53	36.32	36.17
30	33.00	31.44	29.89	30.71	33.96	33.81
40	31.58	30.01	27.10	28.62	31.94	31.64
50	30.09	28.93	24.05	26.60	28.78	28.58
60	28.73	27.92	21.42	24.70	27.49	27.32
70	27.06	26.76	18.18	22.29	26.51	26.40
80	25.33	25.30	14.49	17.65	25.24	25.23
90	20.86	22.22	11.60	10.65	23.35	23.28

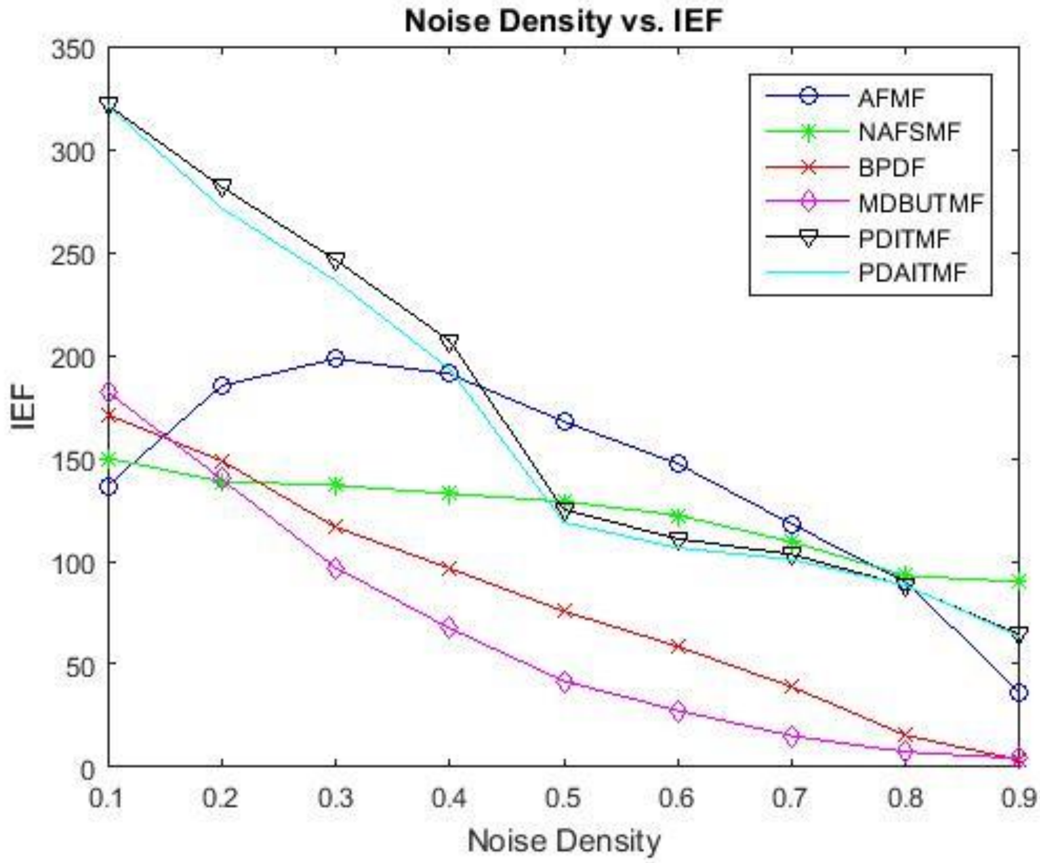


Figure 5.4 Noise density vs IEF graph for different methods.

Table 5.2 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image lena in context to IEF.

ND, %	AFMF	NAFSM	BPDF	MDBUTMF	Proposed PDITMF	Proposed PDAITMF
10	136.6658	149.9737	171.0623	182.2368	321.4951	321.1324
20	185.1743	138.7429	148.8401	139.8670	281.7280	271.4188
30	198.2909	136.7837	116.5665	96.9145	246.1796	236.1613
40	190.8688	132.8139	96.5312	67.4807	206.9795	193.1894
50	167.8436	128.9626	75.7356	41.8114	125.0528	118.8554
60	147.3088	122.3855	58.6326	27.5010	110.9099	106.4913
70	117.9391	109.3478	39.0266	15.1900	103.2783	100.8062
80	89.8729	92.9720	15.4266	7.4257	88.0081	88.2438
90	36.2288	89.9929	3.4506	4.2884	64.2869	63.3766

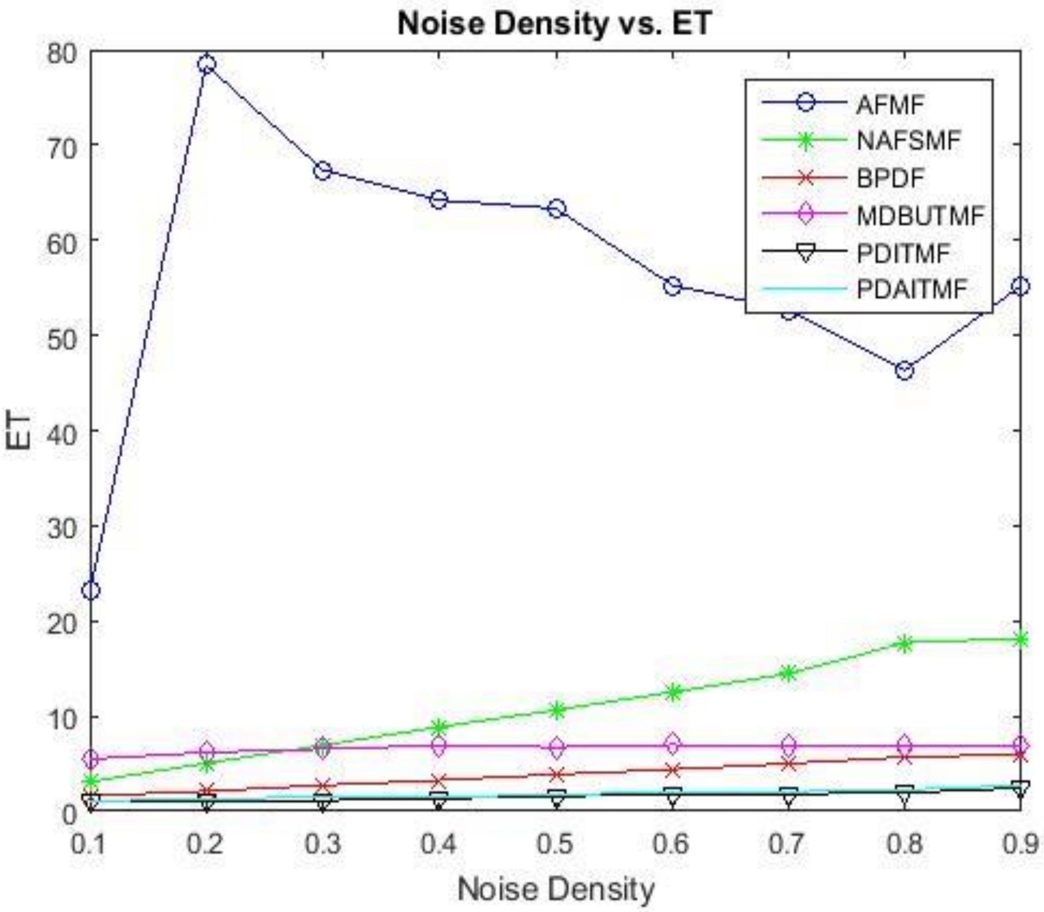


Figure 5.5 Noise density vs ET graph for different methods.

Table 3 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image lena in context to ET.

ND, %	AFMF	NAFSM	BPDF	MDBUTMF	Proposed PDITMF	Proposed PDAITMF
10	23.1394	3.0998	1.6183	5.4978	1.0682	1.0685
20	78.3736	5.0689	2.1264	6.1947	1.0498	1.3377
30	67.4022	6.9429	2.7324	6.5611	1.1381	1.4580
40	64.2149	8.8547	3.2597	6.9152	1.3290	1.5136
50	63.3350	10.6390	3.8845	6.7392	1.5851	1.7473
60	55.2731	12.5278	4.3952	7.0051	1.7667	2.0518
70	52.6843	14.4688	5.0220	6.7927	1.8199	2.0643
80	46.3373	17.7015	5.7071	6.9220	1.9552	2.2484
90	55.2577	18.1870	5.9732	6.7991	2.4443	2.7296

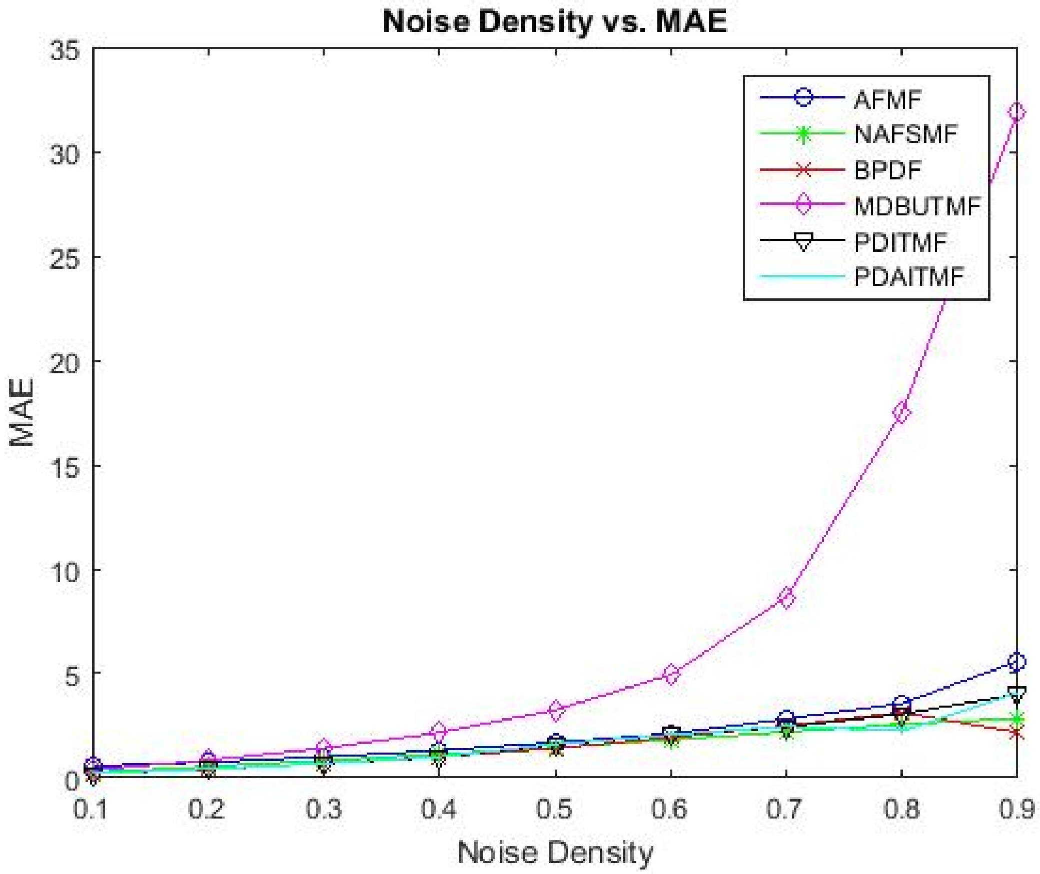
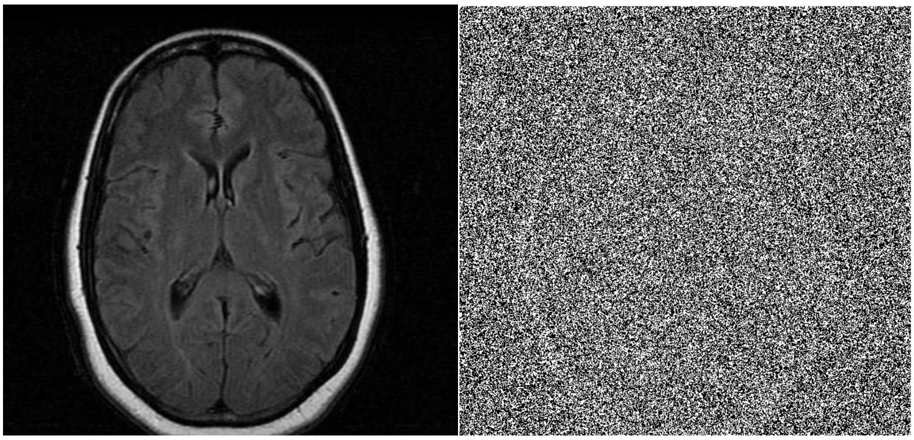


Figure 5.6 Noise density vs MAE graph for different methods.

Table 5.4 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image lena in context to MAE.

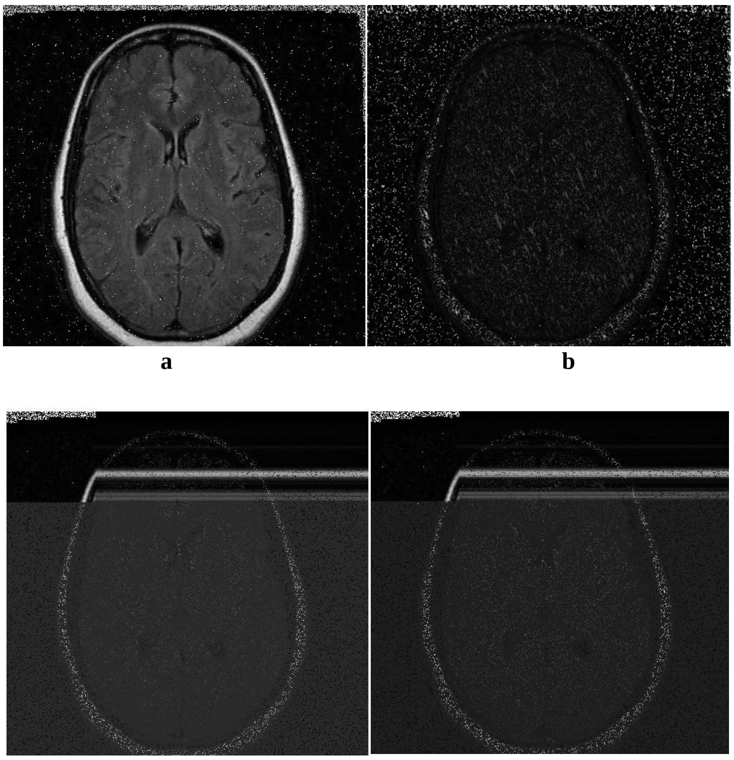
ND, %	AFMF	NAFSM	BPDF	MDBUTMF	Proposed PDITMF	Proposed PDAITMF
10	0.5646	0.2654	0.2038	0.3848	0.2005	0.2064
20	0.7481	0.5411	0.4185	0.8464	0.4308	0.4317
30	1.0043	0.8166	0.6918	1.4192	0.6816	0.6862
40	1.3155	1.1324	1.0176	2.1680	0.9889	1.0087
50	1.6974	1.4527	1.4113	3.2436	1.6020	1.6154
60	2.1125	1.8240	1.9409	4.9410	2.0570	2.0640
70	2.8272	2.1911	2.5009	8.6496	2.4412	2.4665
80	3.5686	2.8688	3.0648	17.5381	3.0608	2.2484
90	5.5893	4.2643	2.1743	31.8645	4.0015	4.0629



a b

Figure 5.7 Comparison of PDAITMF in terms of visual appearance against considered algorithm with 90% ND using image brain.

(a) Original Image (**b**)Noisy Image



a **b**

c **d**

Figure 5.8 Comparison of PDAITMF in terms of visual appearance against considered algorithm with 90% ND using image brain.

(a)NAFSM **(b)**BPDF **(c)**PDITMF **(d)**PDAITMF

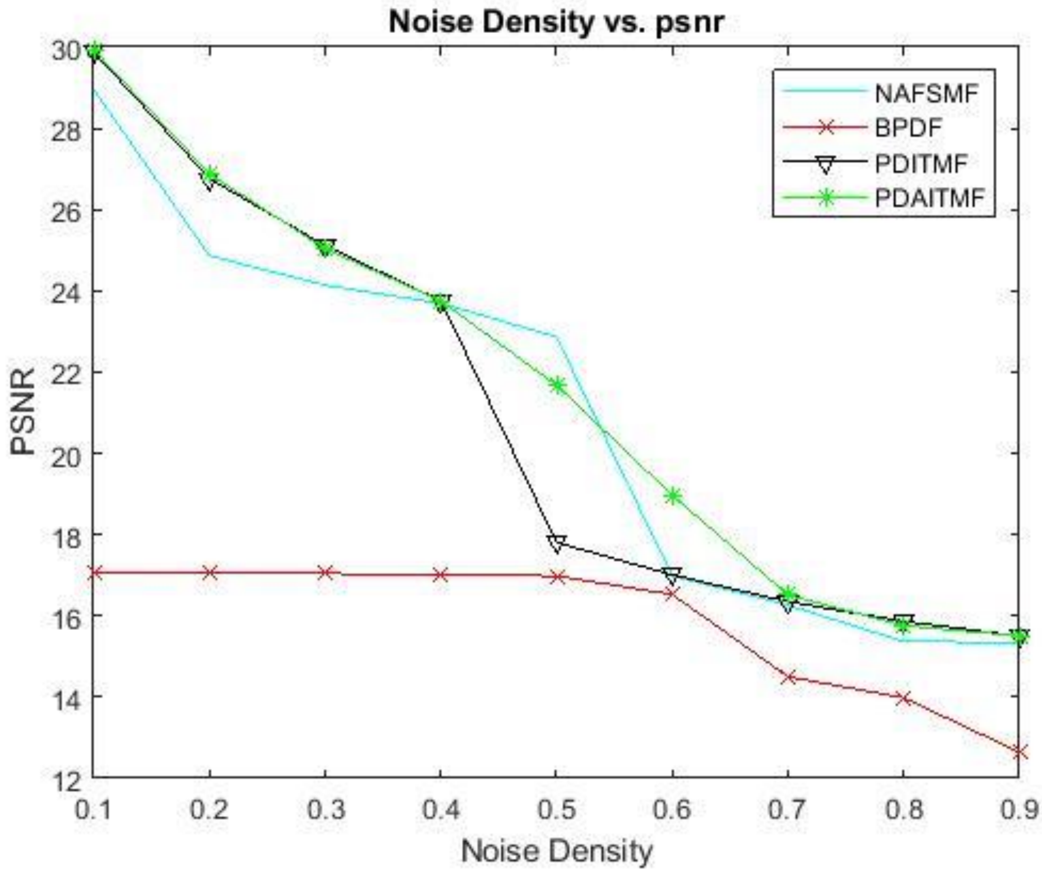


Figure 5.9 Noise density vs PSNR graph for different methods for the image brain.

Table 5.5 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image brain in context to PSNR.

ND, %	NAFSM	BPDF	Proposed PDITMF	Proposed PDAITMF
10	28.9556	17.054	29.8805	29.9393
20	24.8644	17.0468	26.7605	26.8772
30	24.1367	17.0411	25.1162	25.0395
40	23.6936	17.0169	23.7564	23.7527
50	22.8640	16.9808	17.8067	21.6725
60	16.9823	16.5281	17.0094	18.9704
70	16.2637	14.5019	16.3479	16.5162
80	15.3690	13.9823	15.8698	15.7582
90	15.3460	12.6422	15.4995	15.5073

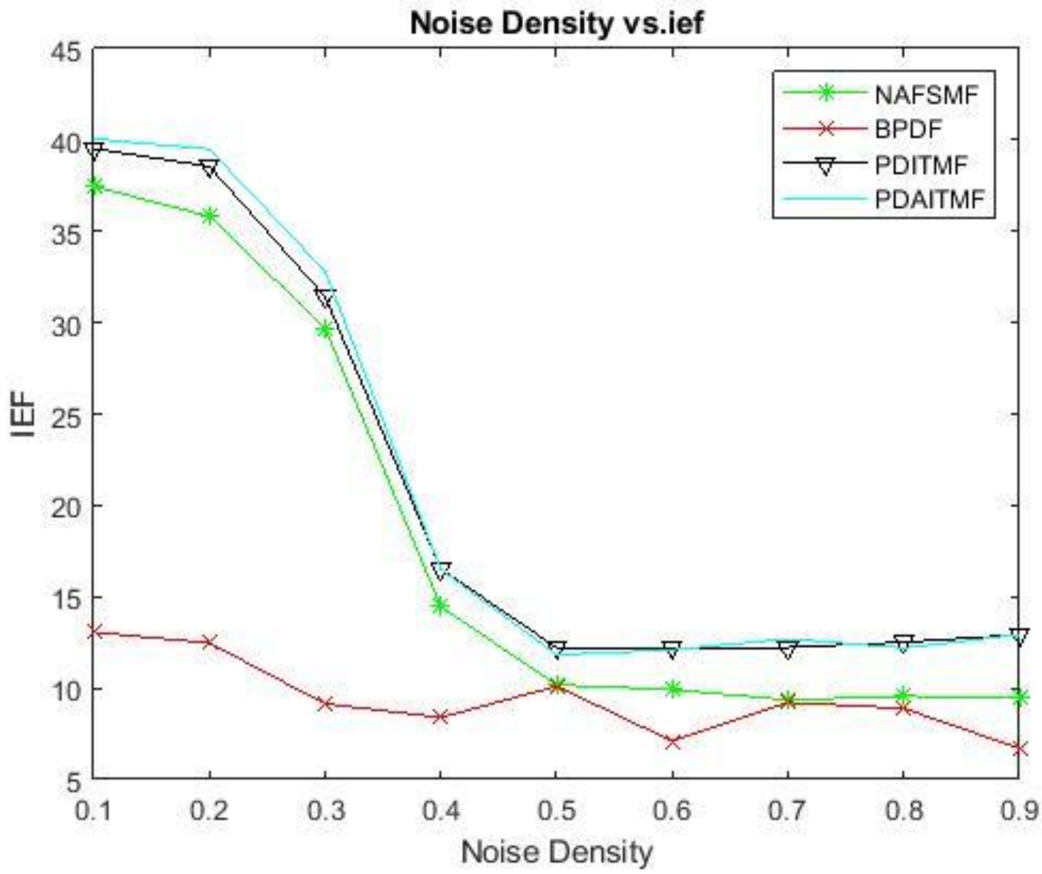


Figure 5.10 Noise density vs IEF graph for different methods for the image brain.

Table 5.6 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image brain in context to IEF.

ND, %	NAFSM	BPDF	Proposed PDITMF	Proposed PDAITMF
10	13.0567	37.456	39.5226	40.0578
20	12.4653	35.816	38.5469	39.4903
30	9.1461	29.6942	31.4135	32.8093
40	8.3891	14.4567	16.5213	16.4961
50	10.1029	10.1762	12.2152	11.8256
60	7.0934	9.9173	12.1952	12.0891
70	9.2158	9.3497	12.2278	12.6958
80	8.8912	9.5561	12.5097	12.1932
90	6.6983	9.4792	12.9206	12.9319

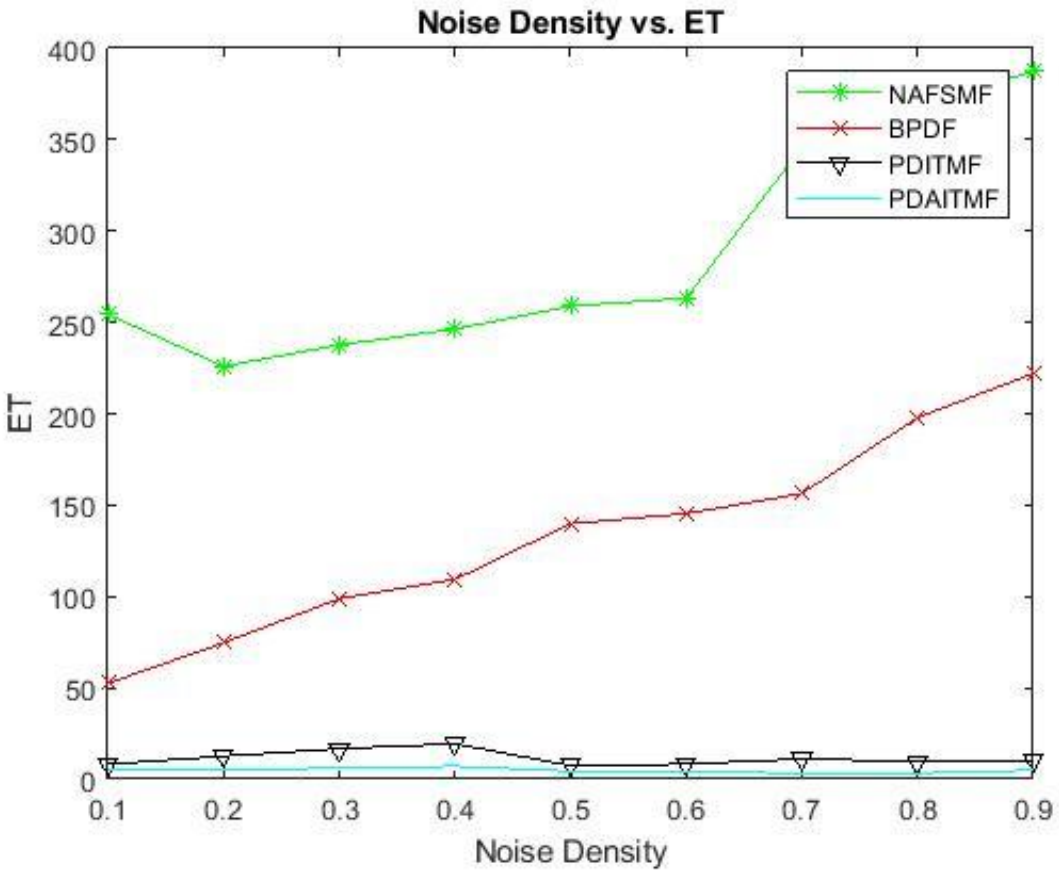


Figure 5.11 Noise density vs ET graph for different methods for the image brain

Table 5.7 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image brain in context to ET.

ND, %	NAFSM	BPDF	Proposed PDITMF	Proposed PDAITMF
10	254.3581	52.4897	8.2075	5.4581
20	225.9596	74.6378	12.5869	5.1018
30	237.6520	98.7799	16.7153	6.0955
40	246.3791	109.3267	19.4039	7.1049
50	258.9323	139.8090	7.3932	4.3471
60	263.2618	145.3654	8.2983	4.3746
70	345.6940	156.3678	11.0758	3.1175
80	369.1358	197.8723	9.7124	3.2913
90	387.3285	221.9921	10.4912	4.8868

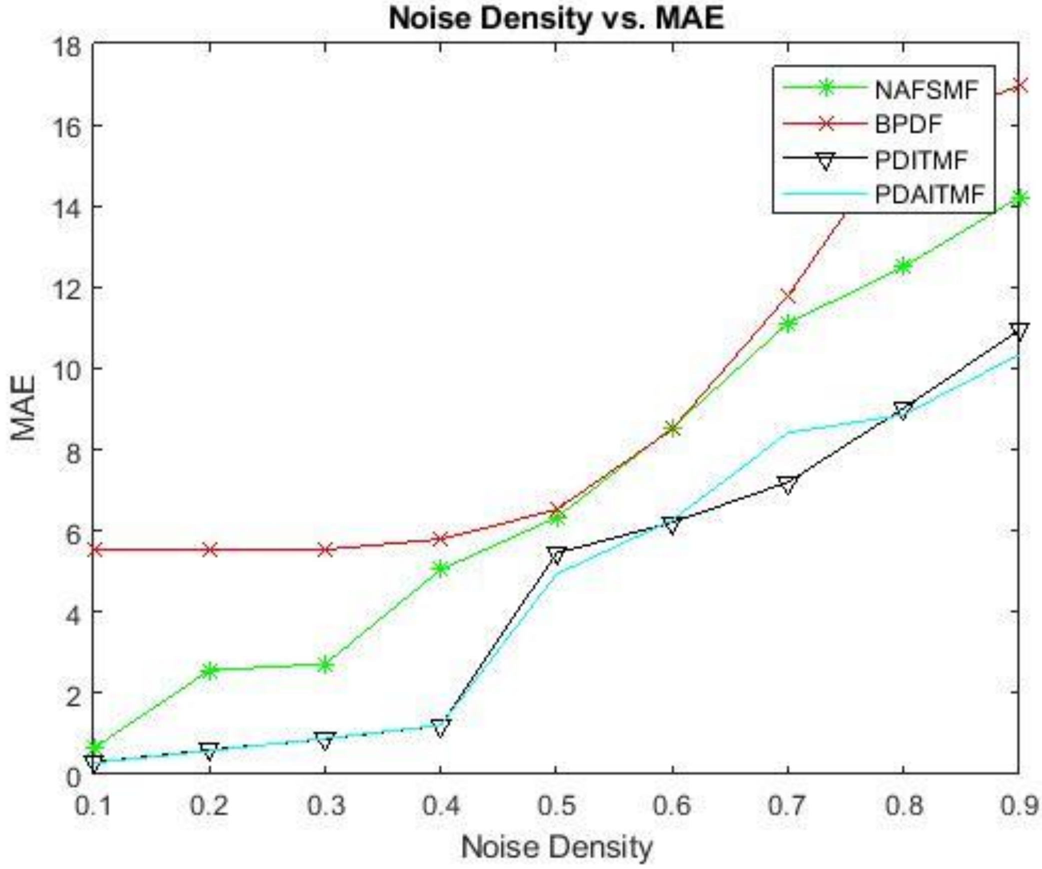
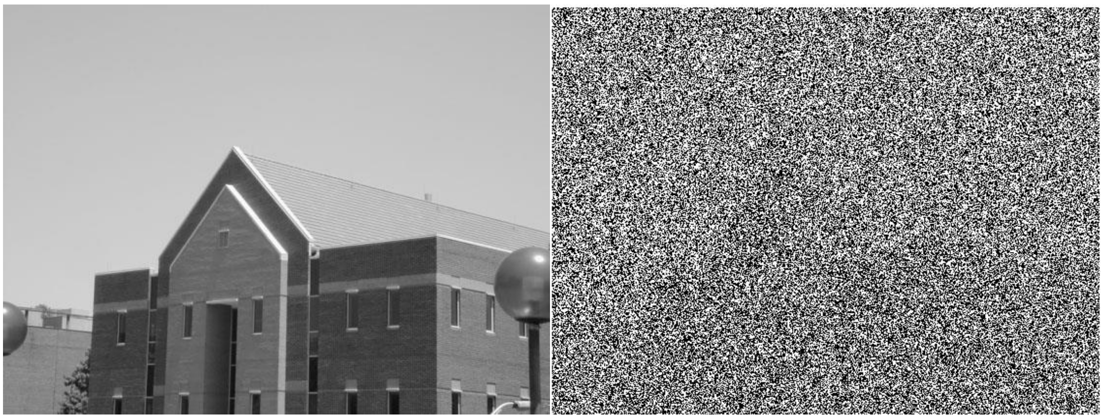


Figure 5.12 Noise density vs MAE graph for different methods for the image brain.

Table 5.8 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image brain in context to MAE.

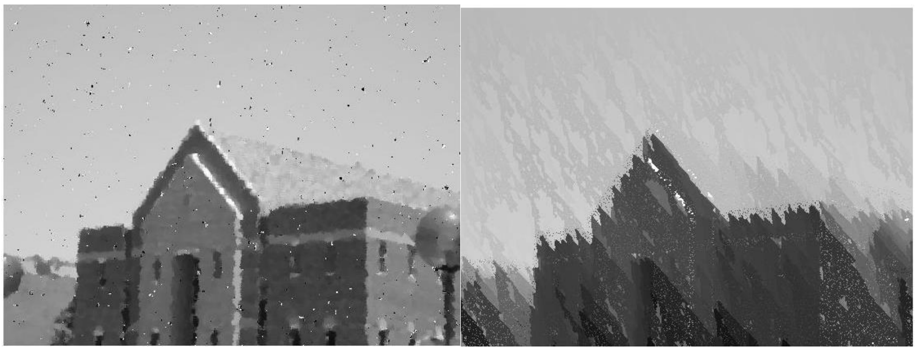
ND, %	NAFSM	BPDF	Proposed PDITMF	Proposed PDAITMF
10	0.6443	5.5511	0.2974	0.2845
20	2.5662	5.5404	0.5981	0.5793
30	2.7198	5.5394	0.879	0.8914
40	5.0456	5.7927	1.2098	1.2108
50	6.3265	6.5191	5.4519	4.9312
60	8.5417	8.5047	6.2043	6.2624
70	11.1122	11.7923	7.1976	8.4138
80	12.4984	15.8812	9.0211	8.8583
90	14.2179	16.9561	10.9464	10.3432



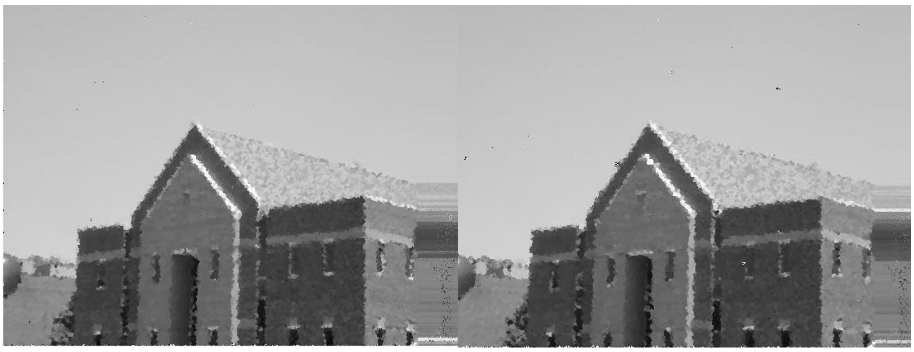
a b

Figure 5.13 Comparison of PDAITMF in terms of visual appearance against considered algorithm with 90% ND using image building.

(a) Original Image **(b)**Noisy Image



a b



c d

Figure 5.14 Comparison of PDAITMF in terms of visual appearance against considered algorithm with 90% ND using image building.

(a)NAFSM **(b)**BPDF **(c)**PDITMF **(d)**PDAITMF

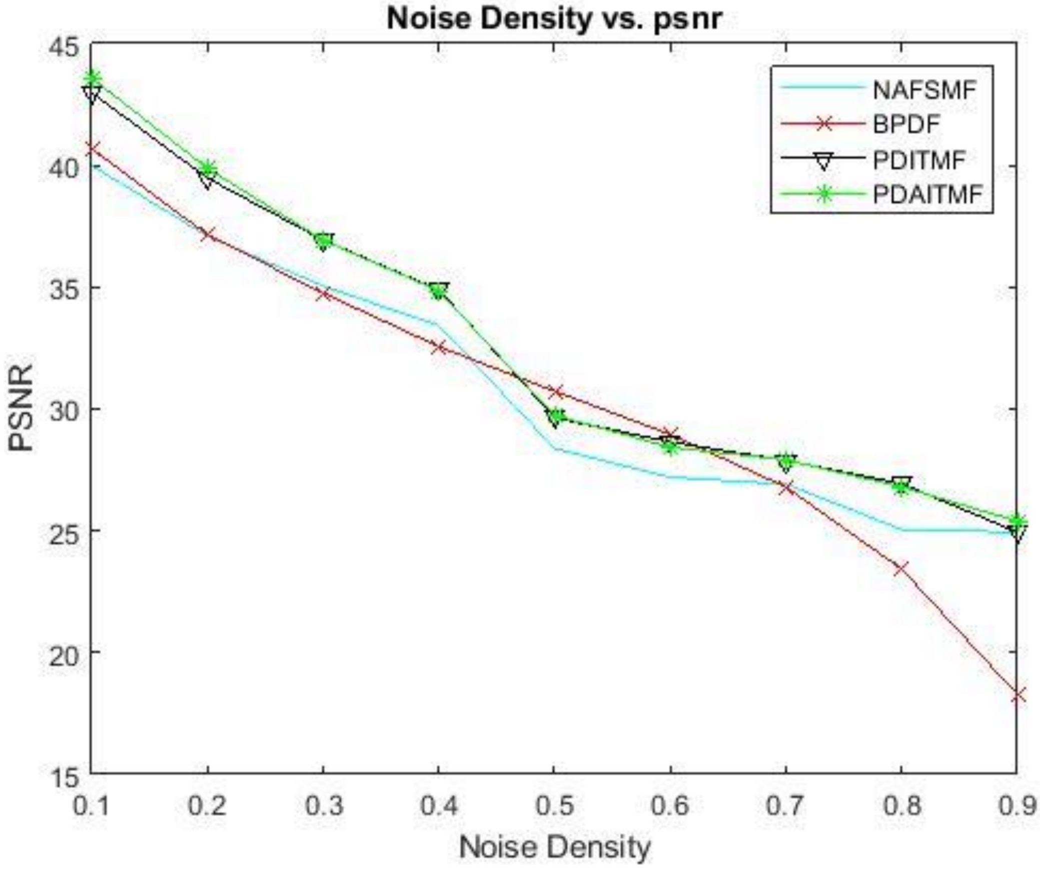


Figure 5.15 Noise density vs PSNR graph for different methods for the image building.

Table 5.9 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image building in context to PSNR.

ND, %	NAFSM	BPDF	Proposed PDITMF	Proposed PDAITMF
10	39.9973	40.692	42.9843	43.5891
20	37.0975	37.1475	39.4739	39.8723
30	35.0439	34.7605	36.9315	36.9259
40	33.4261	32.5593	34.8912	34.8434
50	28.3749	30.7313	29.638	29.7456
60	27.1964	28.9477	28.651	28.429
70	26.9101	26.7958	27.8778	27.9107
80	25.0572	23.4229	26.9331	26.8007
90	24.9408	18.2787	24.9439	25.3883

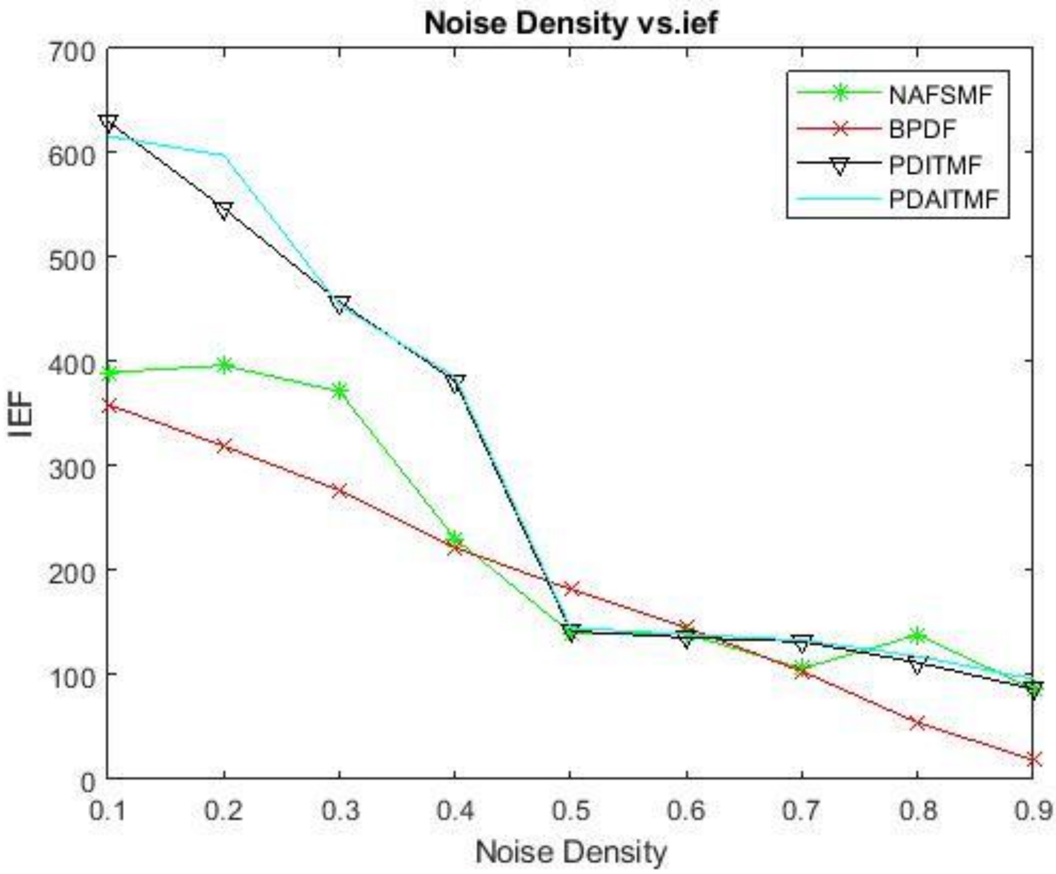


Figure 5.16 Noise density vs IEF graph for different methods for the image building.

Table 5.10 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image building in context to IEF.

ND, %	NAFSM	BPDF	Proposed PDITMF	Proposed PDAITMF
10	389.6574	358.9356	630.0801	616.081
20	396.5759	319.1791	546.9731	597.7123
30	371.4837	276.9363	457.506	454.2272
40	230.4951	221.9755	381.4446	385.3091
50	140.3353	182.1298	141.965	145.1944
60	139.4232	145.4092	135.9593	138.9177
70	106.2437	103.3971	131.927	133.4336
80	138.4347	54.3243	111.8957	117.9058
90	86.5268	18.7056	86.5978	96.196

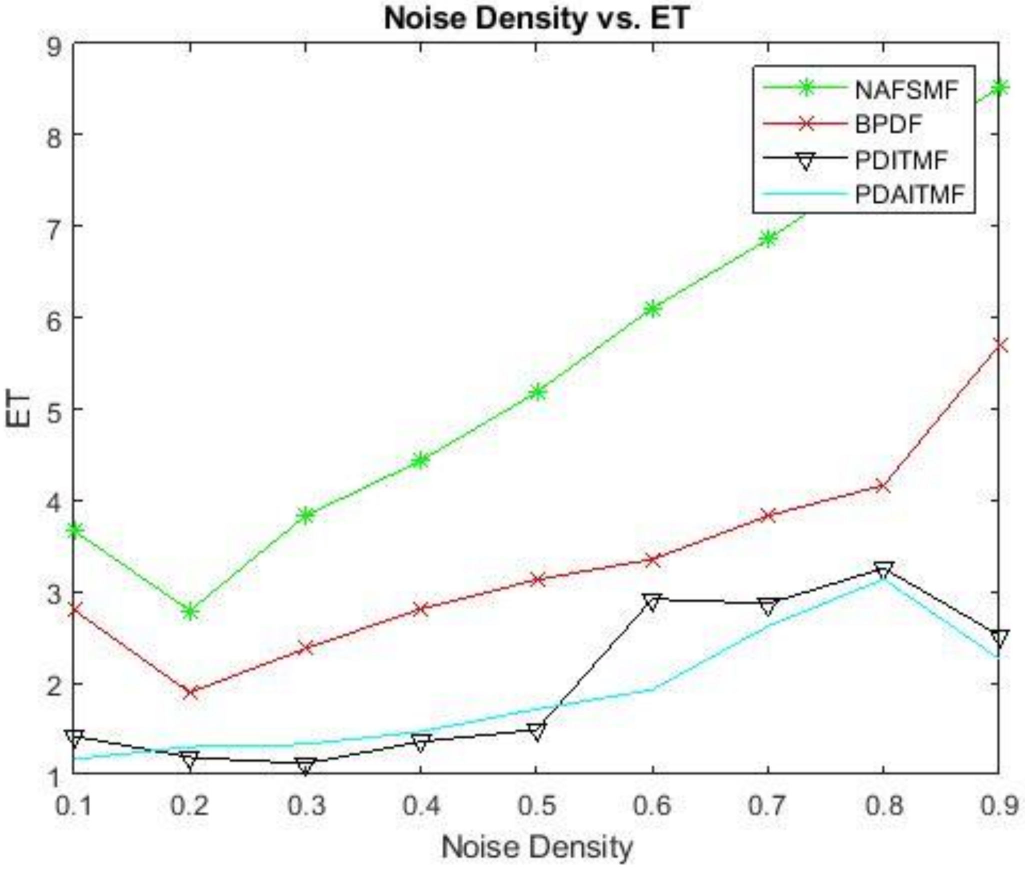


Figure 5.17 Noise density vs ET graph for different methods for the image building.

Table 5.11 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image building in context to ET.

ND, %	NAFSM	BPDF	Proposed PDITMF	Proposed PDAITMF
10	3.6679	2.7988	1.4193	1.1673
20	2.791	1.8971	1.1874	1.302
30	3.8311	2.3761	1.1189	1.3295
40	4.4356	2.8145	1.3592	1.4692
50	5.184	3.1313	1.4899	1.7155
60	6.105	3.3552	2.9198	1.9274
70	6.8543	3.831	2.8702	2.624
80	7.7047	4.1663	3.2565	3.1377
90	8.5169	5.7009	2.5206	2.2632

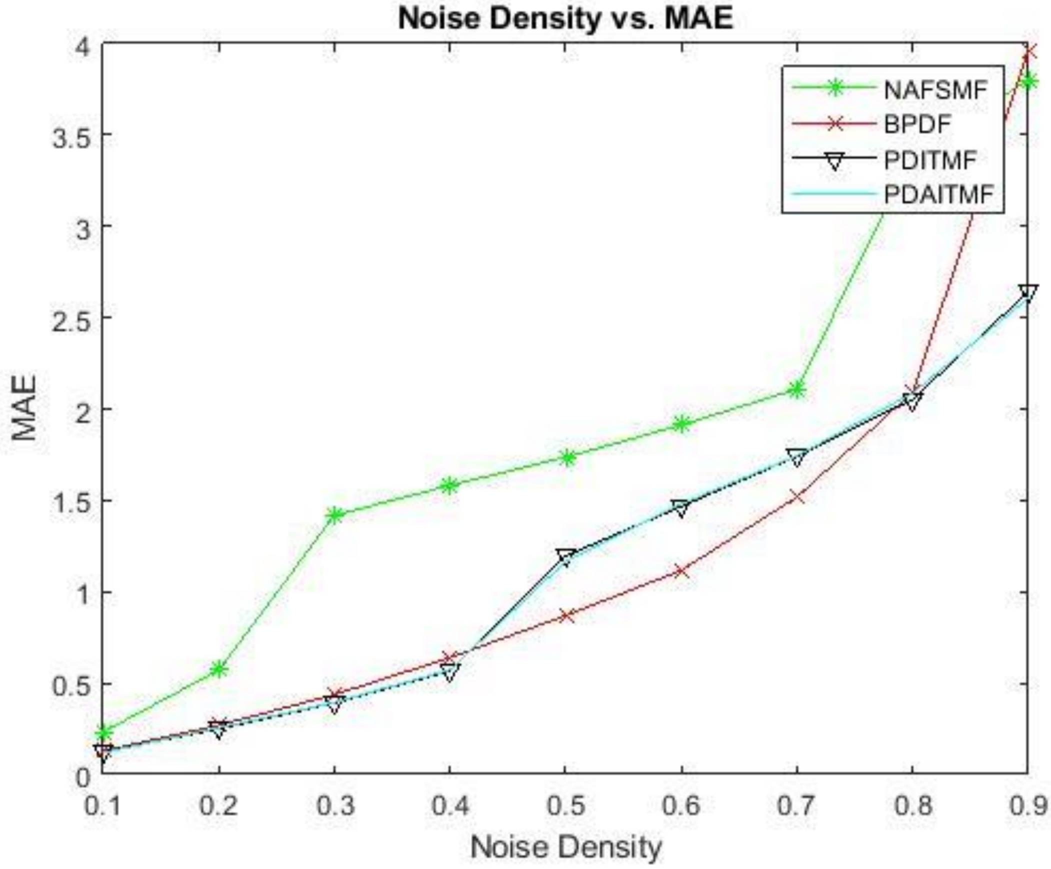


Figure 5.18 Noise density vs MAE graph for different methods for the image building.

Table 5.12 Proposed PDAITMF and proposed PDITMF compared with considered algorithms making use of image building in context to MAE.

ND, %	NAFSM	BPDF	Proposed PDITMF	Proposed PDAITMF
10	0.2317	0.1288	0.1232	0.1192
20	0.572	0.2694	0.2492	0.2555
30	1.4176	0.4368	0.3918	0.3942
40	1.582	0.639	0.5676	0.5728
50	1.7364	0.8699	1.197	1.1665
60	1.9126	1.1171	1.4673	1.4506
70	2.1083	1.5192	1.7419	1.7437
80	3.4008	2.092	2.0533	2.0874
90	3.8011	3.9632	2.6436	2.6079

CHAPTER 6
CONCLUSION

In this paper, a noise detection and expulsion scheme is proposed. The algorithms ITMF and PEITMF are proposed to de-noise an image having low and high NDs, respectively. Finally, both the algorithms are combined together to design a new technique PDAITMF algorithm to de-noise an image contaminated with ‘salt and-pepper’ noise both in low and high NDs. The ITMF algorithm in all respects effectively settle the issue with respect to even number of NFPs in a TMF using a probabilistic methodology. The noise detection scheme is applied in the proposed PDITMF to develop a new technique known as PDAITMF. The PDAITMF technique detects the noisy pixel avoiding misinterpretation of NFP as noisy. Both the proposed PDITMF and PDAITMF are used for evaluation in comparison to the considered algorithms. From the simulation results, it is concluded that the developed algorithm PDAITMF is working effectively in detection and expulsion in extremely low as well as in very high NDs. It is performing efficiently in the case of retaining the edges compared to all other considered state-of-the-art algorithms. The proposed algorithm is exhibiting a notable performance in terms of PSNR as well as an IEF with lower ET at all NDs. The PDAITMF proves itself as an excellent algorithm to be used as a preprocessing technique in image segmentation of many medical images. In future, detection strategy of the Proposed algorithm may be improved more by focusing to range based impulsive noise. This improvement may cover denoising of several other images with a variable noise. For further improvement in computational performance, an hybrid deep CNN model can be
Designed along with proposed algorithm.

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