Digital Image Denoising Using Wavelet Transform and Ant Colony Optimization

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Abstract : Image denoising is a classical and fundamental problem in image processing community. An important challenge in image denoising is to preserve image details while removing noise. Recently, two dimensional (2D) adaptive filter, which can self-adjust the filter coefficients by using an optimization algorithm driven by an error function, has attracted much attention by researchers and practitioners, because 2D adaptive filtering can be employed in many image processing applications, such as image denoising, enhancement and deconvolution. In this project, a new design approach will be employed using two dimensional finite impulse response digital filter using the Ant Colony Optimization for image denoising. The Ant colony optimization algorithm is effective and robust, which helps to yield better denoise performance. Results will be compared with traditional approaches and computer simulation will demonstrate that the proposed method is superior to the conventional methods.

***Index Terms**: Wavelet Transform, Ant Colony Optimization (ACO), Denoising.*

I. Introduction

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. In today's world, image processing area has attracted much attention for scientific as well as its applications and developments. This research field has been used in many areas from medical imaging to geographical application. Moreover, the communication technologies that are based on the sending and receiving the collected images from one point to another point are developed in every day. Datasets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Image Denoising has remained a fundamental problem in the field of image processing. The goal of image denoising is to remove noise as well as preserve useful information. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. So far, there are two basic approaches to image denoising, spatial filtering methods and transform domain filtering methods.

One conventional way to remove noise is to employ spatial filters, which can be further divided into two categories. The first one category is linear spatial filters, such as mean filter and Wiener filter. Mean filter is a sliding window spatial filter that replaces the center value in the window with the average of all the neighboring pixel values together with itself. The larger the size of mask, the more noise filtered, but the more blurred of the image. Wiener filter is a adaptive filter, which is based on assumption that the signal and noise are stationary linear stochastic processes with known spectral characteristics or known cross-correlation and auto-correlation. However, it may cause the unwanted smoothening of the image details since the natural images usually contain smooth areas, textures and edges. Similar to the mean filter, the non-linear spatial filter, such as median filter, replaces the center pixel of the window with the computed median. In recent researches, the improved filter, such as weighted median filter, relaxed median filter have been proposed.

The transform domain filtering methods contains the frequency domain and the wavelet domain. The former often use the low pass filters for denoising. By reducing the high frequency component while preserving the low frequency component, the low pass filtering reduces a large amount of noise at the expense of reducing a small amount of signal. But, to design suitable filter is a challenging issue.

Contrary to the simple spatial or frequency domain method, the wavelet transform method is localized not only in frequency domain but also in spatial domain, which makes it more flexible and effective. Wavelets give a superior performance in image denoising due to properties such as sparsity and multiresolution structure. With Wavelet Transform gaining popularity in the last two decades various algorithms for denoising in wavelet domain were introduced. The focus was shifted from the Spatial and Fourier domain to the Wavelet transform domain.

Over the past decade, wavelet transforms have received a lot of attention from researchers in many several aspects. In the same issue, the discrete wavelet transform also provides multiscale spatial and frequency decomposition. The frequencies can be resolved in space domain and this is very useful in the localization feature of the image that under study.

Recently, two dimensional (2D) digital filters have found a wide range application in the image denoising application, image enhancement, space image processing etc. Consequently, the design approaches of 2D digital filters have attracted quite much attention from practitioners and researchers. The 2D digital filters have found a wide range application in the area of denoising of digital images, image enhancement, seismic and radar signal processing and biomedical image processing. 2D digital filters, like their 1D counterpart, are grouped into two main categories, 2D FIR and 2D IIR digital filters. The 2D

FIR and IIR digital filters are referred to as non-recursive and recursive digital filters, respectively. A 2D IIR filter can achieve a sharper frequency response than 2D FIR digital filter with the same order and this advantage makes it more efficient than the 2D FIR filter. However, the 2D FIR digital filter is more stable than the 2D IIR filter and has linear phase response, which is important in applications of image processing and also it is much easier to implement.

II. LITERATURE SURVEY

Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise is observed in ultrasound images whereas Rician noise affects MRI images. A lot of work has been done in the field of image denoising. Different methods and approaches have been proposed for the elimination of the various noises from the images.

Ever since Donoho's Wavelet based thresholding approach was published in 1995, there was a surge in the denoising papers being published. Although Donoho's concept was not revolutionary, his methods did not require tracking or correlation of the wavelet maxima and minima across the different scales as proposed by Mallat [3]. Thus, there was a renewed interest in wavelet based denoising techniques since Donoho [4] demonstrated a simple approach to a difficult problem. Researchers published different ways to compute the parameters for the thresholding of wavelet coefficients. Data adaptive thresholds [6] were introduced to achieve optimum value of threshold. Later efforts found that substantial improvements in perceptual quality could be obtained by translation invariant methods based on thresholding of an Undecimated Wavelet Transform [7]. An image denoising method based on two dimensional (2- D) finite impulse response (FIR) filtering and differential evolution particle swarm optimization (DEPSO) algorithm was proposed by Jingyu Hua et. al. in [1], where coefficients of the 2-D FIR filter are generated by the DEPSO algorithm. The system is trained with noisy and noiseless images, the generated filters helps to yield better visual quality than the conventional methods and helps to alleviate the noise from digital images.

S. Kockanat et. al. proposed a novel method in which artificial bee colony (ACO) algorithm was adapted to the 2D adaptive filtering and a novel 2D-ACO adaptive filter algorithm was proposed which has a better performance than the other classical adaptive filter algorithms and its denoising efficiency is quite well on noisy images with different characteristics, in [2]. A new design approach that employed the artificial bee colony algorithm for image denoising using two dimensional finite impulse response digital filter is discussed by S. Kockanat et. al. in [3].

A denoising model based on the combination of total variation (TV) and nonlocal similarity in wavelet domain is proposed to suppress the heavy noise and keep the distinct edges of the images in the low light condition, by Yan Shen et. al. in [4]. A novel algorithm for medical image noise reduction based on improving K-SVD and block-matching 3D filtering (BM3D) has been derived by Jing Bai et. al. in [5].

Recently, two dimensional (2D) digital filters have found a wide range application in the image denoising application, image enhancement, space image processing, etc. [6-8]. Abadi et. al. Has used two dimensional adaptive filter algorithms for image denoising [9]. A New Approach of Image Denoising Based on Discrete Wavelet Transform has been proposed by S. H. Ismael et. al. in [10]. Srimanta Mandal et. al. have proposed a multi-scale image denoising method to remove noise while preserving edges in comparison to the state-of-the art approaches in [11].

A comparative study of Progressive Image Denoising (PID), Dual-Domain Image Denoising (DDID) and Block Matching and 3D Filtering (BM3D) for both natural and synthetic images contaminated with different levels of Additive White Gaussian Noise (AWGN) is presented by B.K.Thote et. al. in [12]. Liqiang Shi proposed an improved threshold denoising algorithm which had good denoising effect and high value PSNR (Peak Signal-to-Noise Ratio) was achieved [13].

An efficient method for the umanned aerial vehicle image denoising which integrates an adaptive wavelet thresholding and the image enhancement method is proposed to improve the effect of the wavelet thresholding denoising method and enhance the edge of the image by Fang Liu et. al. [14]. Liwen Dong developed an adaptive denoising technique, which exploits the inter-scale dependencies of wavelet coefficients and compared with the classical threshold method [15]. In 1992, Marco Dorigo initially proposed the Ant Colony Optimisation algorithm in his PhD thesis for the metaheuristic optimization problems [16]. A novel feature selection algorithm based on Ant Colony Optimization (ACO), called Advanced Binary ACO (ABACO), is presented by Shima Kashef et. al. [17],[18] which has a good classification accuracy using a smaller feature set than another existing ACO-based feature selection method.

A. *Wavelet Transform*

The wavelet transform (WT) a powerful tool of signal and image processing that have been successfully used in many scientific fields such as signal processing, image compression, computer graphics, and pattern recognition . On contrary the traditional Fourier Transform, the WT is particularly suitable for the applications of non-stationary signals which may instantaneous vary in time . It is crucial to analyze the time-frequency characteristics of the signals which classified as non-stationary or transient signals in order to understand the exact features of such signals .For this reason, firstly, researchers has concentrated on continuous wavelet transform (CWT) that gives more reliable and detailed time-scale representation rather than the classical short time Fourier transform (STFT) giving a time-frequency representation . The CWT technique expands the signal onto basis functions created by expanding, shrinking and shifting a single prototype function, which named as mother wavelet, specially selected for the signal under considerations. This transformation decomposes the signal into different scales with different levels of resolution. Since a scale parameter shrinking or expanding the mother wavelet in CWT, the result of the transform is time-scale representation. The scale parameter is indirectly related to frequency, when considered the center frequency of mother wavelet.

A mother wavelet has satisfy that it has a zero mean value, which require that the transformation kernel of the wavelet transform compactly supports localization in time, thereby offering the potential to capture the spikes occurring instantly in a short period of time A wavelet expansion is representation of a signal in terms of an orthogonal collection of real-valued generated by applying suitable transformation to the original selected wavelet.

The properties and advantages of a family of wavelets depend upon the mother wavelet features. The expansion is formed by two dimensional expansion of a signal and thus provides a time-frequency localization of the input signal. This implies that most of the energy of the signal will be captured a few coefficient. The basis functions in a wavelet transform are produced from the mother wavelet by scaling and translation operations. When the scaling is chosen as power of two, this kind of wavelet transform is called dyadic-orthonormal wavelet transform, which makes a way for discrete wavelet transform. If the chosen mother wavelet has orthonormal properties, there is no redundancy in the discrete wavelet transforms. In addition, this provides the multi-resolution algorithm decomposing a signal into scales with different time and frequency resolution

B. Digital Image Denoising

Existing noise in digital images causes enormous difficulties in digital image processing applications. Removing any kind of additive noises such as Gaussian noise and Rayleigh noise, and also multiplicative noises which are produced in different stages of image preparation (e.g. image sampling time and transmitting through communication channels) has become a major step in image preprocessing.

Generally, there are two methods for image denoising. First one is based on capturing several images and taking average on them in order to obtain improved image as result and second method is based on post processing for reducing noise [1]. Figure 1 categorizes different image denoising methods.

There is a trade off between denoising an image and losing its edges. Therefore, maintaining edges in the process of image denoising is a critical factor. Numerous image denoising methods have been proposed in the literature based on spatial and temporal filters; some of these methods are brought briefly in the following. In [2], the author has proposed a filter for reducing Gaussian noise in MR images. Spatial filter is a method in which an image is convolved with a filter in spatial domain. This process results in reducing high variations in the image. Awad in [3] has performed image denoising for impulsive noise by using similarity and connectivity between pixels against a random value of noisy pixel. This method distinguishes noisy pixels from the noise free ones. Genetic algorithm has been used in [4] to estimate optimum size and coefficients of spatial window for reducing MSE between original and reconstructed images. Zhang and his colleagues in [6] have proposed a new adaptive image denoising algorithm in the presence of Gaussian noise. Because of its operation in the gradient domain and closeness to Wiener filter, this method is named as gradient-based Wiener filter (GWF). The proposed algorithm is implemented in several iterations and leads to a proper PSNR. Sharif et al. in [7], have used genetic programming on composite filters and have applied morphological operators to perform image denoising. Similar to our method, this method is supervised and is evaluated in terms of PSNR and SSIM in MR images. Image denoising is based on PSO in [8] which improves edge maintaining performance in reconstructed images. In this method, in order to recognize noisy pixels, all pixels in a 5 window are compared with centered pixel in terms of arithmetic absolute difference and intensity. Then median filter is optimized with PSO to restore noisy pixels.

C. Problem Definition

Visual information transmitted in the form of digital image is becoming a major means of communication in modern ages, which is widely used in the application such as remote sensing and biomedical imaging. However, images captured by modern cameras are invariably corrupted by noise either by sensor imperfection, poor illumination or due to the noise introduced by transmitting in noisy channel. However with increasing pixel resolution and more or less the same aperture size, noise suppression has become more relevant. With advances in optics and hardware try to decrease such undesirable effects, software-based denoising approaches are highly considered as they are usually device independent and widely applicable. In the last decade, many such methods have been proposed, leading to considerable improvement in denoising performance.

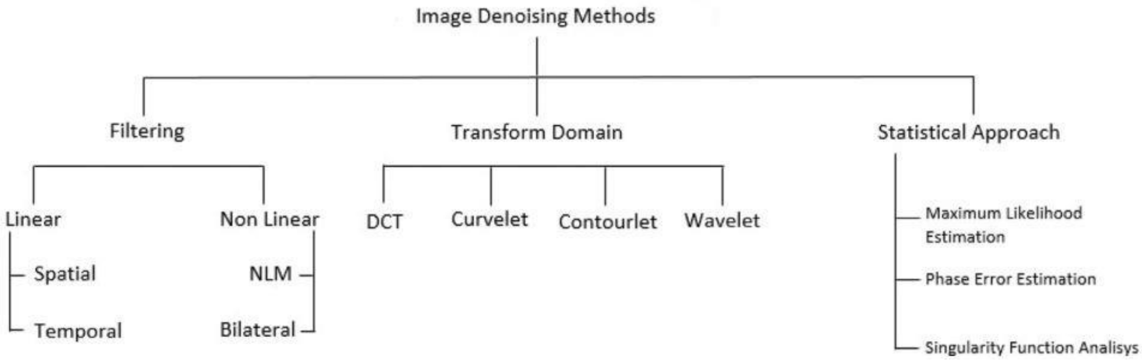


Fig. 1. Classification of medical image denoising methods.

Noise on images is generally undesirable and disturbing. It always plays a negative role on higher level processing tasks such as image registration and segmentation. Thus, how to recover the original visual information as much as possible has become a major concern for decades. Hence, image denoising has become a fundamental step necessarily required for better image understanding and interpretation.

There is a trade-off between denoising an image and losing its edges. When an image is filtered for noise, there is a significant amount of blurring of edges which leads to low quality of denoised images. Therefore, maintaining edges in the process of image denoising is a critical factor. Various image edge detection methods have been proposed in the past. Ant Colony optimization in one such algorithm which can be used to detect and preserve the edge information so as to avoid the smoothening or the blurring of the edges post image denoising.

III. Proposed Methodology

The proposed image edge detection based on ACO combined with wavelet is applied on a 2D image to generate a pheromone matrix. Each entry of that pheromone matrix represents the intensity change in the original image influenced by the edge location. A heuristic matrix is also giving guidance to the algorithm to attain the optimum point easily and in less computation time. The following algorithm applies K number of ants on the image I randomly and then it undergoes N number of iterations and update operation are being done on the pheromone matrix and at last decision is taken on that pheromone matrix to determine the threshold to calculate the edge map. This proposed algorithm is basically divided into four phases: Initialisation, Construction, Update, and Decision phase. Figure 2 sohows the process of denoising.

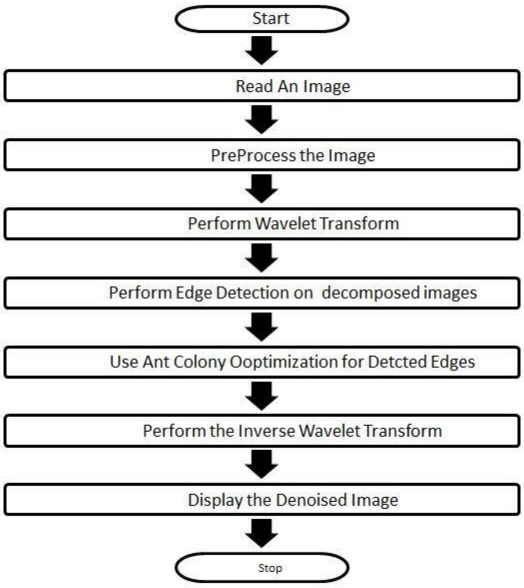


Fig. 2. Flow chart of Proposed algorithm using ACO technique

A. *Wavelet Transform*

The wavelet coefficient can be computed by means of a pyramid transfer algorithm. The algorithms refer to a FIR filter bank with low-pass filter h , high-pass filter g , and down sampling by a factor 2 at each stage of the filter bank. Fig. 1 shows the tree structure of DWT decomposition for three levels. DWT decomposition leads to a

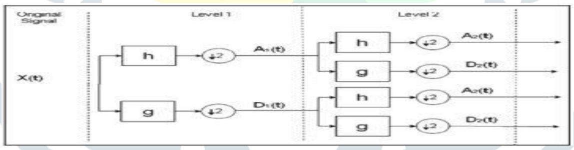


Fig. 3. The DWT decomposition steps of a 1D signal for level of 2

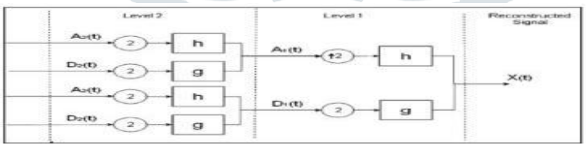


Fig. 4. The DWT reconstruction steps of a 1D signal for level of 2

tree structure as shown in Figure 3 & 4 , where approximation and detail coefficients are presented. In this figure, $\downarrow 2$ *and* $\uparrow 2$ refers to down sampling and up sampling, respectively. This decomposition sometimes called as sub-band coding. The low pass filter produces the approximation of the signal, and the high pass filers represent the details or its high frequency components. The decomposition successively can be applied on the low frequency components, approximation coefficients, in DWT. In 2D case, the image signal is considered as rows and columns as if they are one dimentional signals. In DWT, firstly the each rows of the image is filtered, then the each columns are filtered as in 1D case. Figure 3 demonstare the decompositon of an image for one level. As in signal decomposition, after each filtering, the subsampling is realized. The result of this process gives four images; approximation, horizantal details, vertical details and diagonal details. Because of subsampling after each filtering, the result subimages of the original image has the quarter size of the original image.

B. *Edge Detection*

Edge detection techniques transform images to edge images benefiting from the changes of gray tones in the images. Edges are the sign of lack of continuity, and ending. As a result of this transformation, edge image is obtained without encountering any changes in physical qualities of the main image. Objects consist of numerous parts of different color levels. In an image with different gray levels, despite an obvious change in the gray levels of the object, the shape of the image can be distinguished in Figure 5(a)5(b)5(c)5(d)

An Edge in an image is a significant local change in the image intensity, usually associated with a discontinuity in either the image intensity or the first derivative of the image intensity. Discontinuities in the image intensity can be either Step edge, where the image intensity abruptly changes from one value on one side of the discontinuity to a different value on the opposite side, or Line Edges, where the image intensity abruptly changes value but then returns to the starting value within some short distance. However, Step and Line edges are rare in real images. Because of low frequency components or the smoothing introduced by most sensing devices, sharp discontinuities rarely exist in real signals. Step edges become Ramp Edges and Line Edges become Roof edges, where intensity changes are not instantaneous but occur over a finite distance[10]. Illustrations of these edge shapes are shown in Figure 5(a) 5(b) 5(c) 5(d)

C. *Ant Colony Optimization*

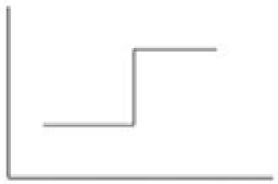
This proposed algorithm is basically divided into four phases: Initialisation, Construction, Update, and Decision phase.

1) Initialisation Phase: Input image I of dimension M is taken as input which works as a solution space for the artificial ants. The K number of ants are moved over the whole image such that the every pixel of the image is covered by an ant. A pheromone matrix of dimension, same as that of the image, is taken and initialized to a very small value t init.

2) Construction Phase: At each and every n_{th} construction step, one ant being randomly selected from K ants and it move over the image for L movement steps. Ant move from the pixel (l,m) to pixel (i,j) with a probability transition rule

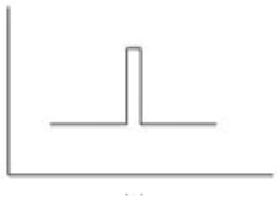
3) Update Phase: The updation is done on the pheromone matrix, first time after each ant is within n th construction loop and the second update process occurs after each and every ant have completed the n th construction loop where The local update broadens the search for the subsequent ants by reducing the pheromone level on the traversed edges. This way it provides an opportunity for the subsequent ants to produce necessary solutions. Therefore, the chance of repetition becomes less likely in the same iteration .

4) Decision Phase: In this phase, the output pheromone matrix so obtained undergoes a threshold calculation procedure. This work proposes a F-ratio based technique for determination of optimum threshold value which is further used for converting the resultant pheromone matrix to binary edge map. F-ratio is a statistical measure in the



(a) Step Edge

(b) Ramp Edge



(c) Line Edge

(d) Roof Edge Fig. 5. Types of Edges

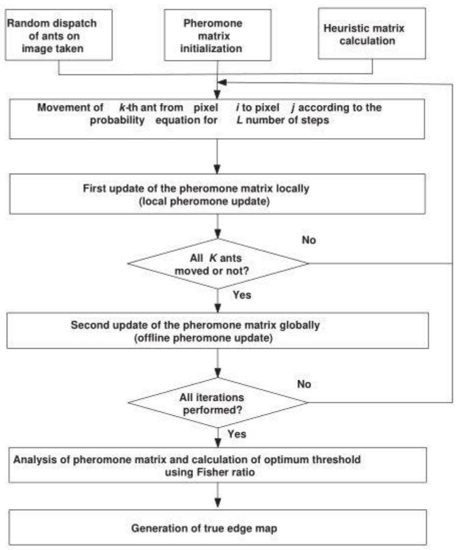


Fig. 6. Flow chart of Proposed algorithm using ACO technique

analysis of variance for multi-cluster data. It is defined as

$$F - ratio = \frac{Variance\ of\ means\ between\ the\ clusters}{Average\ Variance\ with\ in\ the\ clusters} \quad (1)$$

If all data points is segmented into two cluster based on their value using a threshold T then F-ratio can be represented as

$$F - ratio_T = \frac{(\mu_{1T} - \mu_{2T})^2}{2 \cdot (\nu_{1T}}$$

where μ_{1T} , μ_{2T} , ν_{1T} , ν_{2T} are the mean and variance of the cluster 1 and cluster 2 respec- tively. The proposed F-ratio based optimum threshold calculation algorithm is as follows

1) Initially, using a threshold T based on intensity level, total elements of pheromone matrix is segmented into two classes C_1 and C_2, where C_1 and C_2 consists of all data points having intensity level below and above T respectively.
2) Compute F - ratio T for all possible threshold T.
3) The optimum threshold $T*$ is determined as the value of T for which F - ratio T maximizes.

The calculated optimum threshold T_* is finally utilized to get the binary edge map from updated pheromone matrix.

IV. Experimental Results

The images were simulated with the help of Matlab software running on computer system with configuration pentium i7 processor, 3 GB RAM, 500 GB HDD. The results are as follows:

- Figure 7(a) & 7(b) shows the original image and image after adding the gaussian noise to the image.
- Figure 8(a), 8(b) & 8(c) shows the images of DWT in which 4 outputs are expected at an angle of 0^o&180^o, 45^o,±135^o ± and based on approximations.
- Figure 9(a), 9(b) & 9(c) shows the outputs of all DWT images after thresholding which is used to remove he noisy pixels
- Figure 10(a), 10(b) & 10(c) shows the outputs of all DWT images after thresholded images optimized by the Ant Colony Optimization.
- Figure 11(a), 11(b) & 11(c)shows the original image and image after adding the gaussian noise to the image and the reconstructed image.
- Figure 11(d) shows the statistical results for the original image and image after adding the gaussian noise to the image and the reconstructed image.

V. CONCLUSION

In this paper, the artificial Ant Colony Optimization (ACO) algorithm was adapted to the 2D adaptive filtering and a novel 2D-ACO adaptive filter algorithm was firstly proposed in literature. The novel 2D-ACO adaptive filter algorithm has a unique place in terms of describing 2D adaptive filter algorithm based on metaheuristic algorithms. In order to demonstrate the efficiency and the performance of the 2D-ACO adaptive filter algorithm, it was firstly applied to the 2D-ANC setup for image noise filtering. To make a fairly comparison, all conditions were determined as recommend in literature. The performance of the 2D-ACO adaptive filter algorithms was compared with those of the other classical algorithms. The input and output PSNR and SSIM values were calculated to measure the image quality between the denoised and original test images. The results show that the best output PSNR and SSIM values were obtained by using 2D-ACO adaptive filter algorithm. Also, the effect of the 2D FIR filter order was analyzed for varying filter orders.

The improved adaptive denoising approach was successfully worked for Speckle noise filtering using the novel 2D- ACO adaptive filter algorithm and its greatest advantage is that there is no need a complex transform or method, such as wavelet or Fourier domain transform, adaptive or non-adaptive thresholding methods or fuzzy based algorithms. As a result, both the novel 2D-ACO adaptive filter algorithm and improved adaptive denoising approach bring a valuable innovation to 2D signal processing applications.

As a future study, we intend to combine the novel 2D-ACO adaptive filter algorithm with set-membership (SM) and selective partial update (SPU) approaches for achieving low computational complexity and short execution time. Also, not only will be used the novel 2D-ACO adaptive filter algorithm for image denoising applications but also for widespread applications in 2D signal processing, such as adaptive line enhancement or channel estimation.

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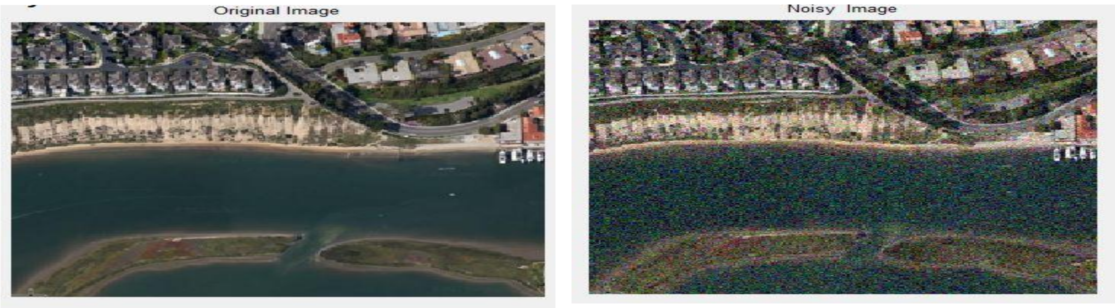
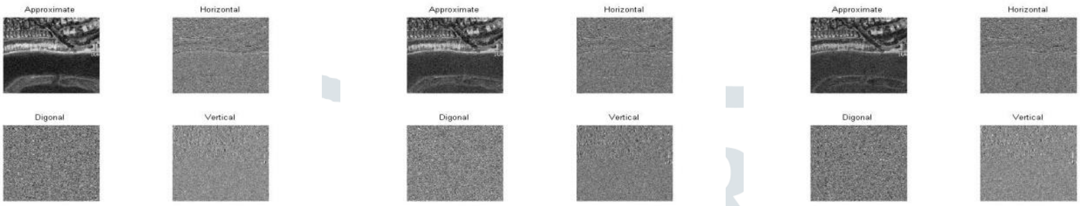
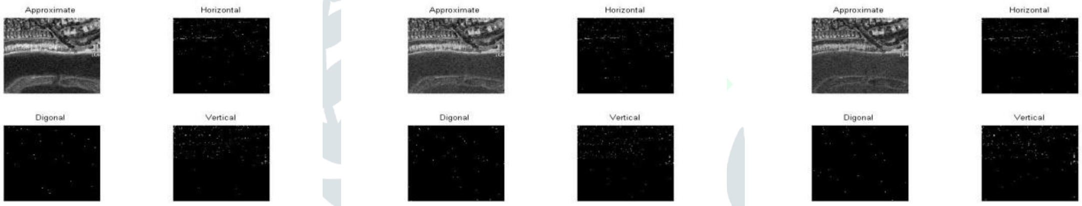


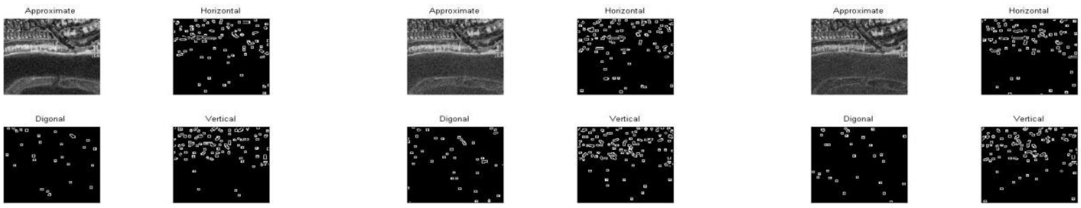
(a) Original Image (b) Original Image + Noise Fig. 7. Step 1 : Reading and Processing the Image



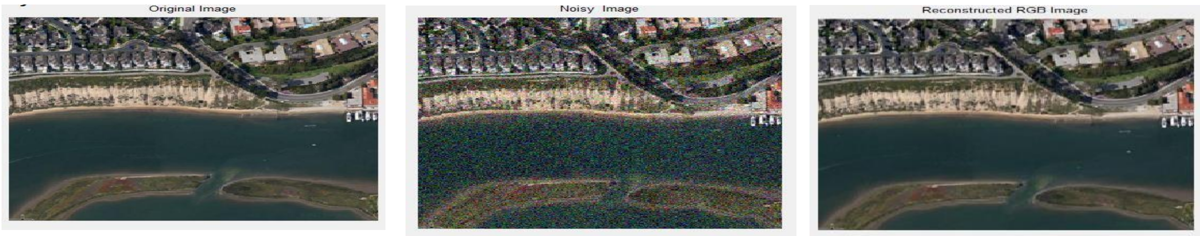
(a) DWT of Red Plane Image (b) DWT of Green Plane Image (c) DWT of Blue Plane Image Fig. 8. Step II : Descrete Wavelet Transform of Image



(a) Thresholded Red Channle Image (b) Thresholded Red Channle Image (c) Thresholded Red Channle Image Fig. 9. Step III : Thresholding of DWT images to presere Edges



Optimised by ACO Red Channel Image (b) Optimised by ACO Green Channel Image (c) Optimised by ACO Blue Channel Image Fig. 10. Step IV : Optimized Images by ACO



(a) Original Image (b) Original Image + Noise (c) Reconstructed Image

PSNR	39.9315	SNR	30.7593	SSIM	0.99886

(d) Statistical Results Fig. 11. step V: Final Result