# Image Denoising with Nonlinear Hybrid Diffusion-Modified Perona-Malik Model (NHD-MPM) and Parameter Optimization by Artificial Bee Colony (ABC) Algorithm

[1]Shiyamala. A, Research scholar, Department of Computer Science and Applications,
Providence college for women, coonoor. E-mail: shyamala472@gmail.com
[2]K.B.Manikandan, M.C.A., M.Phil., (Ph.D), Assistant Professor, Department of computer science and applications, Providence College for women, coonoor.

**ABSTRACT**: Image denoising aims to faithfully reconstruct an image from its noise corrupted observation. It tends to improve the degraded image quality for better interpretation and data extraction. Anisotropic diffusion models have reached a good balance between noise removal and edge preserving. But the optimization of the parameters for these models becomes difficult because of the different images and their quality. In this paper, a proposed a hybrid image denoising algorithm based on Nonlinear Hybrid Diffusion -Modified Perona-Malik (NHD-MPM) model. It is performed based on the mean curvature smoothing and Gaussian heat diffusion. The results of this denoising algorithm are combined to diffusion model and the Modified Perona- Malik (MPM) model. In addition the proposed work parameters of the Nonlinear Hybrid Diffusion are optimized via the use of the Artificial Bee Colony (ABC) optimization. In addition, the patch similarity modulus is used as the new structure indicator for the MPM model. The proposed method is thus able to efficiently preserve the edges, textures, thin lines, weak edges, and fine details, meanwhile preventing the staircase effects. Also compared NHD-MPM model with some recently advanced models, the experimental results demonstrated NHD-MPM model has a better detail and texture preservation capability.

**INDEX TERMS:** Image denoising, Nonlinear Hybrid Diffusion -Modified Perona-Malik Model (NHD-MPM), Anisotropic diffusion, Artificial Bee Colony (ABC), and parameter optimization.

## 1. INTRODUCTION

Image processing is dominant tool for many fields including facial recognition, robotic vision, artificial intelligence, security surveillance, and medical imaging (Chen et al 2014). The complete recital of image processing systems based on test image quality. Nonetheless, image is unavoidably corrupted by noise during transmission and acquisition. Image denoising attempts to faithfully reconstruct an image from its noise corrupted region. It tends to enhance degraded image quality for superior interpretation and data extraction. Henceforth, image denoising is a principal problem and a significant process for numerous image processing schemes (Chatterjee and Milanfar 2010). Is Denoising Dead? . Image denoising has turns to be an attractive research field from last decades (Chen, Y.,et al 2016). The researchers acquired that partial differential equations (PDEs) have important effectiveness in image de-noising field.

Currently, numerous PDE-based replicas for image denoising have been anticipated, like isotropic diffusion (ID) model (Perona-Malik 1990) (PM), total variation (TV) model (Rudin et al 1992) (Levine 1979) and so on. Among these replicas, isotropic diffusion (ID) model anticipated by Witkin A. P.Witkin, Scale-Space Filtering is pioneer of PDE-based replicas for noise elimination. (Perona and Malik 1990) introduced a well-organized anisotropic diffusion replica based on PDE, termed PM model. PM replica is initial investigation on anisotropic diffusion replica for image restoration. Image Selective Smoothing and Edge Detection by Nonlinear Diffusion, from these models, TV model is thriving anisotropic diffusion model sourced on PDE for image denoising. The complete, these anisotropic diffusion replicas have attained finest balance amongst edge preserving and noise removal.

Although second-order PDE-based anisotropic diffusion replicas possess good capability to reduce noise while preserving edges, they emerge to have numerous drawbacks like staircase effects. (Catté et al 1992) projects modified PM model that outperforms pre-denoising by Gaussian filter before every iteration. (Barbu et al. 2009) describes general variation replica for image de-noising and restoration, which is sourced on minimization of convex function of gradient under reduced growth conditions. (Ziou and Horé 2012) anticipated powerful diffusion procedure (i.e., DPM model) that can abridge and improve performance of PM model. DPM model integrates directional diffusion and inverse diffusivity to considerably decrease aliasing around step edges and lines, for now preserving uniform regions. These replicas control diffusion procedure by gradient function, without target to preserve weak edges, thin lines, and fine details.

To make full utilization of advantages of PM model, ID model and second order directional derivative, we enhanced PM model and ID model using second order directional derivative, correspondingly. A weighting function sourced on patch similarity modulus is cast off to balance relative weights of modified PM model and modified ID model. This hybrid replica extracts structure of original image and diffuses along edge's tangential direction of original image. By taking benefits from modified ID (e.g., the performance for removing noise and edge-preserving is concurrently enhanced) and modified PM (e.g., the patch similarity modulus to serve as structure indicator), realized image de-noising in flat region and diminishing aliasing and noise around edges, for now preserving thin lines, textures, weak edges, and fine details. Furthermore, staircase effects are considerably prevented. In this investigation, anticipated hybrid image de-noising procedure based on Nonlinear Hybrid Diffusion -Modified Perona-Malik (NHD-MPM) model. It is carried out based on Gaussian heat diffusion and mean curvature smoothing. As well, the anticipated work factors of Nonlinear Hybrid Diffusion are optimized through Artificial Bee Colony (ABC) optimization utilization.

## 2. LITERATURE REVIEW

Ji et al (2013) anticipated a novel edge detection indicator, i.e. diffusivity function. Owing to this diffusivity function, novel diffusion is forward-backward and non-linear anisotropic. Similarly, Perona-Malik (PM) diffusion, novel forward-backward diffusion is modifiable and manageable. At last, with explicit difference scheme (PM scheme) and inherent difference scheme, numerical experiments for different images are performed, correspondingly.

Babu (2013) anticipates two diverse ratio-based edge identification inspired extensions to Speckle Reducing Anisotropic Diffusion (SRAD). One amongst the anticipated extensions integrates an edge-sensitive boosting factor to assist Laplacian operator based edge detector of SRAD and gradient. Edge-sensitive boosting factor is distinct by global edge information offered by ratio based edge detector. The anticipated diffusion function is weighted sum of two components – (1) global ratio-based edge identification inspired component and (2) unique diffusion function of SRAD. A general scaling function selection approach for both extensions and larger window size utilization for gathering local statistics have also been anticipated. The proposed filters cast off significant enhancement in edge preservation and speckle de-noising.

Atlas et al (2014) dealt with mathematical and numerical investigation of variation replica of image de-noising equation derived from Perona–Malik equation. Diffusion resulting from anticipated model is combination of Perona–Malik and p-Laplacian operators. The uniqueness and existence of asymptotic behaviour as $p \to \infty$ of proposed replica are determined. Also provides certain numerical implementation details and proves effectiveness and efficacy of model.

Prasath and Vorotnikov (2014) measured class of weighted anisotropic diffusion PDEs. By assuming an adaptive factor within usual divergence procedure, retained powerful de-noising capability of anisotropic diffusion PDE devoid of any oscillating artefacts. A well-balanced flow version of anticipated system is measured which adds an adaptive fidelity term to general diffusion term. To demonstrate benefits of anticipated methodology offers certain examples, which are functional in restoring real digital images and noisy synthetic. A comparison investigation with subsequent anisotropic diffusion based systems highlight superiority of proposed process.

Ogada et al (2014) anticipated an alternative structure for total variation based on image de-noising replicas. The model is sourced on minimization of total variation with functional co-efficient, in this case, functional coefficient is function of magnitude of image gradient. Also illustrated effectiveness of model selected based on anticipated consideration. As well, for illustrative replica, proves uniqueness and existence of minimizer of variational crisis. The uniqueness and existence of solution related evolution equation are also performed. Outcomes are in co-operated to reveal effectiveness of selected replica in image restoration over conventional techniques of PM, D-α-PM, Total Variation (TV) method.

Liu et al (2016) anticipates hybrid regularizers-based adaptive anisotropic diffusion to eradicate stair casing effect for total variation filter and synchronously evade edges blurring for fourth-order PDE filter. In anticipated replica, $H$-1-norm is measured as regularization term and fidelity term is composed of complete fourth-order filter and variation regularization. The two filters can be adaptively chosen based on diffusion function. When pixels locate at edges, total variation filter is chosen to filter image, which can conserve edges. When pixels belong to flat regions, fourth-order filter is accepted to smooth image, which can eradiate staircase artifacts. As well, divide Bregman and relaxation methods are employed in numerical procedure to speed up computation.

Karami et al (2017) spotlights on numerical technique of crisis termed Perona-Malik inequality which is utilized for image denoising. This replica is acquired as Perona-Malik model and $p$-Laplacian operator with $p \to \infty$. To limit this, an efficient procedure is cast off which is amalgamation of traditional additive operator splitting and nonlinear relaxation procedure presented outcomes in image filtering which illustrate effectiveness and efficiency of procedure and at last compared it with prevailing techniques.

Yuan and Wang (2016) anticipated novel diffusion coefficient which is grounded on local entropy information and second order derivative for image de-noising. In the anticipated model, second order derivative term is initiated, which diminishes stair-casing effect and maintains edge in processed image. Local entropy information can preserve texture. Perona–Malik replica with novel diffusion coefficient enhances de-noised effects, and eliminates edges from being over-smoothed. The anticipated model acquires more satisfied outcomes than other two prevailing models.

Maulik and San (2016) initiates relaxation filtering closure method to account for sub-grid scale effects in explicitly filtered large eddy simulations by anisotropic diffusion idea. Also cast off Perona-Malik diffusion replica and reveal its shock capturing capability and spectral recital for resolving Burgers turbulence problem, which is easier prototype for more sensible turbulent flows demonstrating similar quadratic nonlinearity. In contrast relaxation filtering methods, it is also demonstrated that huge inertial range can be attained by anticipated anisotropic diffusion replica by compact stencil system in a proficient way.

Romdhane et al (2016) proposed novel technique for 3D Computed Tomography (CT) denoising sourced on Coherence Enhancing Diffusion replica. De-noising step for CT images is a significant challenge in medical image processing. These images are corrupted by noise and low resolution. Quantitative measures like PSNR are evaluated to phantom CT image to enhance proposed model efficiently, in contrast to number of de-noising algorithms. Moreover, 3D CT data illustrate that this method is promising and effective in eliminating noise and preserving details.

Loum et al (2017) anticipated hybrid diffusion techniques based on Jeffreys-Type Equation (JTE). The technique proposed offers two steps: pre-smoothing stage termed Adaptive-Linear Diffusion (A-LD) and smoothing stage termed Jeffreys Anisotropic Diffusion (JAD). A stopping criterion for A-LD, termed Variance Absolute Error (VAE) which calculates noise level, is anticipated to assure optimality of smoothing filter. A diffusion function is anticipated to take into account blurring induced by pre-smoothing. The anticipaed hybrid technique is compared with Perona and Malick, telegraph equation; artefact concealed Xu-AD and large-scale non-local means models. The anticipated hybrid technique is capable both on noise reduction and preservation of fine structures and contours.

## 3. PROPOSED METHODOLOGY

A nonlinear hybrid diffusion equation is discussed for image denoising, which is a combination of mean curvature smoothing and Gaussian heat diffusion. First, propose a new edge detection indicator, that is, the diffusivity function. Based on this diffusivity function, the new diffusion is nonlinear anisotropic and forward-backward. Unlike the Perona-Malik (PM) diffusion, the new forward-backward diffusion is adjustable and under control. Then, the existence, uniqueness, and long-time behavior of the new regularization equation of the model are established. Finally, using the explicit difference scheme (PM scheme) and implicit difference scheme (AOS scheme), do numerical experiments for different images, respectively. Experimental results illustrate the effectiveness of the new model with respect to other known models. Image restoration and smoothing are important in problems ranging from medical diagnostic tests to defense applications such as target recognition. Over the past 20 years, the use of variational methods and nonlinear partial differential equations (PDEs) has significantly grown and evolved to address the image restoration problem. The overall representation of the proposed work is shown in figure 1.

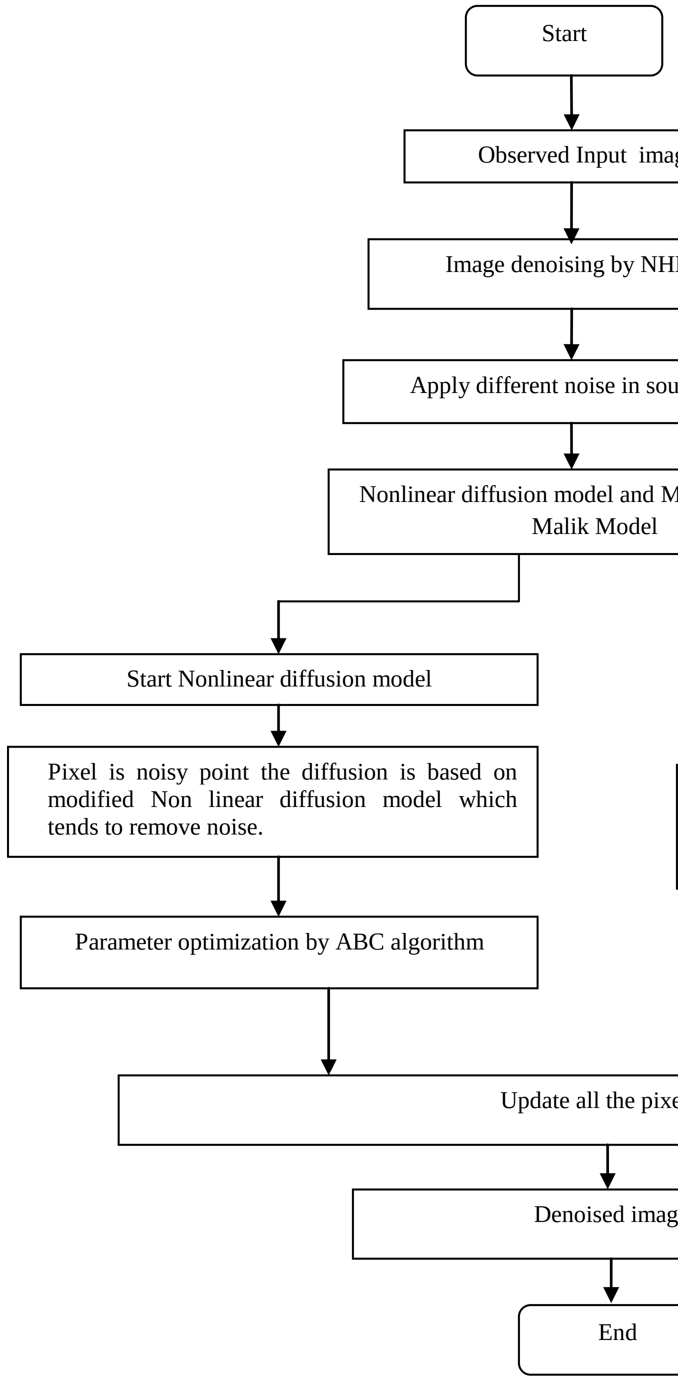


**Figure 1 .Flow chart for the Proposed System**

### 3.1. NONLINEAR HYBRID DIFFUSION

Let $u_0$ be the intensity of an image obtained from a noiseless image by adding Gaussian noise with zero mean, defined on a rectangle $\Omega \in \mathbb{R}^2$, and let represent the reconstructed image. The problem is to recover the restoration image , from the observed, noisy image $u_0$, where the two are related by $u$

A large number of image restoration techniques are conveniently formulated using some nonlinear partial differential equations (PDEs) approach. The review article [69] V. Caselles, J.-M. Morel, G. Sapiro, and A. Tannenbaum, Introduction To The Special Issue On Partial Differential Equations And Geometry-Driven Diffusion In Image Processing And Analysis, provides a historical description of the use of PDEs in image processing. In (Perona-Malik 1990) developed an anisotropic diffusion scheme for image denoising. The basic idea of this nonlinear smoothing scheme was to smooth the image while preserving the edges in it. This was done by using equation

$$c|\nabla_u|) \quad (1)$$

$$u(0,x) = f, \quad (2)$$

where f is the noisy image and is the image to be smoothed and describes its evolution over time. The diffusivity $c(|\nabla u|)$ controls the amount of diffusion. $c(\ )$ is also an edge indicator and a smooth nonincreasing function and has such properties as

$\geq 0,$, and $c \to 0$, as $s \to \infty$. This ensures that strong edges are less blurred by the diffusion filter than noise and low-contrast details.

In (Iijima 1962), Iijima employs the following linear diffusivity function:

$$(|x|) = 1 \quad (3)$$

the model is linear isotropic diffusion, it cannot preserve the edge and some features. The PM diffusivity function (Perona-Malik 1990) is usually

$$(|x|) \quad \frac{}{+|x^2|/} \quad (4)$$

The PM diffusion is nonlinear anisotropic diffusion and can preserve the most features, especially edges in the image. Here are some of the previously employed diffusivity functions. (Charbonnier et al 1994)

$$c(|x|) = \frac{}{\sqrt{\ +|x|^2}} \quad (5)$$

TV diffusivity (Andreu et al 2001)

$$c(|x|) = \frac{1}{|x|} \quad (6)$$

Weickert diffusivity(Alvarez et al 1992):

$$c(|x|) = \begin{cases} \\ \text{xp}\left(\frac{}{|x|^8}\right), |x| \end{cases} \quad (7)$$

To make the images more pleasing to the eye, it would be useful to reduce staircasing effect. Many models to reduce this effect have been proposed in the literature. A simple adjustment with practical applications is to include a short range modifier in the nonlinear diffusion (Andreu et al 2001). The new well-posed equation is given by

$$— \quad (|\nabla \quad u|) \quad (8)$$

$$u(0,x) = \quad \Omega, \quad (9)$$

$$— \quad \Omega \quad (10)$$

$$c(|\nabla_u|) = \frac{}{|\nabla_u|^2} \quad (11)$$

$$c(|\nabla_u|) = \exp\left(-\frac{|\nabla_u|^2}{}\right) \quad (12)$$

where K is the Gaussian kernel

### 3.2 PM MODEL

In order to well preserve edges while removing noise, Perona and Malik proposed the anisotropic PM model based on the ID model:

$$\begin{cases} — \quad (|\nabla_u|) \\ \quad )| \end{cases} \quad (13)$$

where $c(.)$ is the diffusion coefficient. Generally, $c(.)$ is a nonnegative and monotone non-increasing function over the gradient magnitude. Accordingly, the diffusion coefficient is able to adaptively control the diffusion speed, making it possible to distinguish the edges of image and decrease the diffusion in the edge regions. The diffusion coefficient c(.) satisfies such requirements in that: c(0) = 1. Perona and Malik suggested the following two diffusion coefficients:

$$c(|\nabla_u|) = \frac{}{|\nabla_u|^2} \quad (14)$$

$$c(|\nabla_u|) = \exp\left(-\frac{|\nabla_u|^2}{}\right) \quad (15)$$

where the gradient threshold $k$ plays an important role in restoring an image and determining the smoothing level. If the $k$ value is too large, the diffusion process will over smooth and result in a blurred image. By contrast, if the $k$ value is too small, the diffusion process will stop smoothing in early iterations and yield a restored image that is similar to the original one (Chao 2010) The selection of gradient threshold $k$ was discussed in (Tsiotsios and Petrou 2013).

However, the PM diffusion model is very sensitive to noise. When the noise intensity is large, the gradient of the noise is similar to the gradient of the edge, so the PM diffusion model cannot distinguish between the true edge of the image and the false edge caused by noise. This is the primary reason that the PM model easily generates the staircase effects. Besides, the PM model is not suitable to reduce aliasing found on edges, as mentioned in (Ziou and Horé 2012), Reducing Aliasing In Images: A PDE-Based Diffusion Revisited.

### 4.3 MPM MODEL

The MPM (Wang et al 2013) Signal Process,model aimed at preserving edges and suppressing staircases simultaneously in the PM model, which was a direct generalization of the PM model using directional Laplacian. It diffuses image along the edge direction of the original image.

$$— \quad \vec{n} \quad (|\nabla_u|) \quad )\vec{n} \quad (|\nabla_u|) \qquad (16)$$

where $\vec{n}$ indicates the diffusion direction and

$|\nabla_u|) = \frac{}{\sqrt{\ +|\nabla_u|}}$

A novel denoising model based on second order directional derivative is proposed by us in this section, namely the DLHPDE model. It combined the advantages of ID model, PM model and second order directional derivative. Additionally, we selected the patch similarity modulus as the new structure indicator in the proposed model. We used the patch similarity idea described in 79 to quantify the patch similarity modulus between neighboring patches. Let and $P_{\acute{x},\acute{y}}$ be the two patches centered at pixel (located at (x,y) on the image u) and its neighbor pixel $\acute{}\,\acute{}$ (located at $(\acute{x},\acute{y},)$on the image u). The two patches can be described as:

(17)

$$\acute{}\,\acute{y} \quad \acute{x}- \quad \acute{y}- \quad \acute{}\,\acute{y} \quad \acute{x}+ \quad \acute{y}+ \quad \acute{}$$

(18)

then the patch similarity modulus between and $P_{\acute{x},\acute{y}}$ be is calculated as follows:

$$d(P \quad \acute{}\,\acute{}) \quad -(\Sigma \quad \acute{}\,\acute{y} \quad )$$

(19)

where the size of patch is $p$ X $p(p = 2q + 1)$ and q is set to 1, the $P_{x,y}(m)$ represents the $m_{th}$ element of $P$ and the $P_{\acute{x},\acute{y}}\ (m)$ represents the $m_{th}$ element of $P_{\acute{x},\acute{y}}$ . The image patch can effectively and accurately represent the structure information. Therefore, the new structure indicator based on patch similarity modulus can identify not only the strong edges, weak edges or textures, but also the noise. The initial form of the proposed model can be expressed as:

$$— \quad \nabla\left(c\left(d\left(P \quad \acute{}\,\acute{}\right)\right)\nabla_{\mathrm{u}}\right)$$

(20)

where $\theta \epsilon [0,1]$ is the weighting function, patch similarity modulus $d(P_{x,y}, P_{\acute{x},\acute{y}})$ is the structure indicator.

To better preserve edges and reduce the aliasing and the noise around edges, we employed the second order directional derivative [80] Y. Wang, W. Ren, and H. Wang, "Anisotropic Second And Fourth Order Diffusion Models Based On Convolutional Virtual Electric Field For Image Denoising, to modify proposed model. Since the second order directional derivative [81]may be written as:

$$— \quad \vec{n} \quad u\vec{n} \qquad (21)$$

where $\vec{n}$ is a unit vector, $T$ is the transposition, and $H = \nabla^T\nabla_u$ is the Hessian matrix. The defined expression $\vec{n}H\vec{n}^T$ is the second order directional derivative of the image *u(x,y )*along a given vector .So the proposed model can be further rewritten as follows:

$$— \quad \theta\vec{n} \quad u\vec{n} \quad )\vec{n}$$

$$\left(c\left(d\left(P \quad \acute{}\,\acute{}\right)\right)\nabla_{\mathrm{u}}\right)\vec{n}$$

$$\Big( \quad -\Big| \quad \Omega$$

(22)

where Ω is the support of the noisy image $f\,(x, y)$, Ω is the boundary of the image $N$ is an unit outward normal to Ω.

$$\frac{}{*\Sigma_{P\,\acute{}\,\acute{y}\in\delta}\left(d\left(P \quad \acute{}\,\acute{y}\right)\right)} \qquad (23)$$

$$\acute{}\,\acute{y} \quad \frac{}{\acute{}\,\acute{y})} \qquad (24)$$

where $\alpha$ is a small parameter, $\delta$ represents the neighboring patches of $P_{x,y}$, and these patches centered at the four neighbors of pixel $u_{x,y}$, $k$ is the patch similarity modulus threshold.

### 3.4 ARTIFICIAL BEE COLONY ALGORITHM

In the ABC model, the colony consists of three groups of bees: employed bees, onlookers and scouts. It is assumed that there is only one artificial employed bee for each food source. In other words, the number of employed bees in the colony is equal to the number of food sources around the hive. Employed bees go to their food source and come back to hive and dance on this area. The employed bee whose food source has been abandoned becomes a scout and starts to search for finding a new food source. Onlookers watch the dances of employed bees and choose food sources depending on dances. The main steps of the algorithm are given below

- Initial food sources are produced for all employed bees
- REPEAT
- Each employed bee goes to a food source in her memory and determines a closest source, then evaluates its nectar amount and dances in the hive
- Each onlooker watches the dance of employed bees and chooses one of their sources depending on the dances, and then goes to that source. After choosing a neighbour around that, she evaluates its nectar amount.

- Abandoned food sources are determined and are replaced with the new food sources discovered by scouts.
- The best food source found so far is registered.
- UNTIL (requirements are met)

In ABC, a population based algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees is equal to the number of solutions in the population. At the first step, a randomly distributed initial population (food source positions) is generated. After initialization, the population is subjected to repeat the cycles of the search processes of the employed, onlooker, and scout bees, respectively. An employed bee produces a modification on the source position in her memory and discovers a new food source position.

Provided that the nectar amount of the new one is higher than that of the previous source, the bee memorizes the new source position and forgets the old one. Otherwise she keeps the position of the one in her memory. After all employed bees complete the search process, they share the position information of the sources with the onlookers on the dance area. Each onlooker evaluates the nectar information taken from all employed bees and then chooses a food source depending on the nectar amounts of sources. As in the case of the employed bee, she produces a modification on the source position in her memory and checks its nectar amount. Providing that its nectar is higher than that of the previous one, the bee memorizes the new position and forgets the old one. The sources abandoned are determined and new sources are randomly produced to be replaced with the abandoned ones by artificial scouts.

Artificial bee colony (ABC) algorithm is an optimization technique that simulates the foraging behavior of honey bees, and has been successfully applied to various practical problems. ABC belongs to the group of swarm intelligence algorithms.

A set of honey bees, called swarm, can successfully accomplish tasks through social cooperation. In the ABC algorithm, there are three types of bees: employed bees, onlooker bees, and scout bees. The employed bees search food around the food source in their memory; meanwhile they share the information of these food sources to the onlooker bees.

The onlooker bees tend to select good food sources from those found by the employed bees. The food source that has higher quality (fitness) will have a large chance to be selected by the onlooker bees than the one of lower quality. The scout bees are translated from a few employed bees, which abandon their food sources and search new ones.

In the ABC algorithm, the first half of the swarm consists of employed bees, and the second half constitutes the onlooker bees. The number of employed bees or the onlooker bees is equal to the number of solutions in the swarm. The ABC generates a randomly distributed initial population of SN solutions (food sources), where SN denotes the swarm size.

By utilizing the information given by a randomly selected potential solution inside the existing swarm, every potential solution updates itself in ABC. Here, a step size, defined as a linear combination of a random number $\Phi$ $[-1, 1]$, existing solution and a randomly selected solution were utilized. The quality of the updated solution functions depending on the step size. If the step size is excessively large, this occurs if the variations of current solution and randomly chosen solution is large enough with extreme absolute value of $\Phi_{ij}$, then the updated solution can beat the true solution and if the step size is excessively small then the convergence rate of ABC may reduce desirably. Proper balances of the step sizes can compensate the ability of the exploration and exploitation of the ABC algorithm at the same time. But, this step has random component, so its balance can't be performed manually. The Improved solution update strategy based on the fitness of the solution, the exploration and exploitation can be balanced. In the general ABC, the food sources are updated, as shown in equation (25).

(25)

Where $v_{ij}$ is defined as the changes made on enhancing the parameter j, that is, $x_{ij}$ is changed. Indices j and k are random variables. Changes to the present solution (food source) are done by employed bees in the employed bee phase, which works upon the details of the individual experience and the new solution fitness value.

If the fitness value of the new solution is higher than the old solution, then the bee updates the position to the new solution and old one will be rejected. The position update equation for i$^{th}$ candidate in this phase is

$$\{ \quad (x \quad ) \qquad (26)$$

Where $k \in \{1, 2, \dots SN\}$ and are randomly selected indices. $k$ Should vary from $i$. is a random number between $[-1, 1]$. To enhance the exploitation, it is required to consider the details of the global best solution, in order to train the search of candidate solutions, the solution search equation is examined by equation (27) and it is improved as follows:

$$(x \quad ) \qquad (27)$$

The fitness based self adaptive mutation method is included in the general ABC, to progress the capacity of the exploitation. The perturbation in the solution is based on the fitness of the solution that occurs in the proposed approach. It is clear that the number of update in the dimensions of the

$i^{th}$ solution works on $prob_i$ and it implies nothing but a function of fitness.

This technique is based on the suggestion that the perturbation will be high for low fit solutions as for that the value of $prob_i$ will be low as long as the perturbation in high fit solutions will be low because of the high value of $prob_i$. It is pictured that the global optima should be closer to the better fit solutions and if the perturbation of better solutions is high, then we have an option of skipping the true solutions because of its huge step size. So, the step sizes, which were correspondingly based.

The perturbations in the solution, are fewer for good solutions and it is high for worst solutions and it is answerable for exploration. So, in the proposed approach, the better solutions will be accomplished in the search space as long as the low fit solutions.

*Step 1: Start*

*Step 2 : Observe the input noisy image*

*Step 3: Image denoising by proposed Nonlinear Hybrid Diffusion -Modified Perona-Malik Model (NHD-MPM)*

*Step 4: Apply different noise in source image*

*Step 5: Start Nonlinear diffusion model*

*Step 5.1: Pixel is noisy point the diffusion is based on modified Non linear diffusion model which tends to remove noise.*

*Step 6: Start Modified Perona-Malik Model.*

*Step 6.1: The pixel is on the edge, the diffusion is based on MPM model which tends to preserve edge.*

*Step 7: Parameter optimization by ABC algorithm*

*Step 8: The gray value of the pixel finally changes as step 5 & step 6.*

*Step 9: Update all the pixels in image.*

*Step 10 : Finally got the denoised image.*

*Step 11: End*

## 4. RESUTLS AND DISCUSSION

In this experiment, input image as shown in Figure 2. The salt and Pepper noise image is shown in figure 3. The denoised image of the MPM is shown in figure 4. The noise removed image results of the NHD-MPM is shown in figure 5 input image as shown in Figure 6. The Gaussian noise image is shown in figure 7. The denoised image of the MPM is shown in figure 8. The noise removed image results of the NHD-MPM is shown in figure 9 input image as shown in Figure 10. The Speckle noise image is shown in figure 11. The denoised image of the MPM is shown in figure 12. The noise removed image results of the NHD-MPM is shown in figure 13.

**Figure 2. Input Image**

**Figure 3. Salt and Pepper Noise**

Figure 4. MPM Denoise Image

Figure 5. NHD-MPM Denoise

Figure 6. Input Image

Figure 7. Gaussian Noise

Figure 8. MPM Denoise

Figure 9. NHD-MPM Denoise

**Figure 10. Input Image**

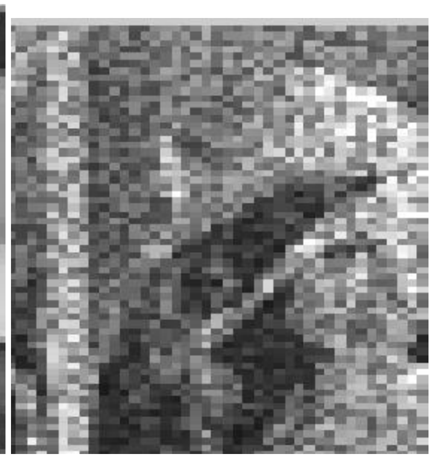

**Figure 11. speckle noise**

**Figure 12. MPM denoise**

**Figure 13. NHD-MPM denoise**

The performance of proposed technique is evaluated by imperceptibility and robustness. Imperceptibility is measured by Mean Square Error (MSE) defined by:

$$— \sum \sum |g \qquad )| \tag{28}$$

$$\overline{\qquad} \quad — \Sigma \quad \Sigma_{j=0}^{N-1}(g \qquad )) \tag{29}$$

where $g(i; j)$ denotes the pixel value of the original image and $f\,(i; j)$ implies the pixel value of the compressed image.

**Table 1. Performance comparison results of image denoising methods**

| Metrics | Existing (MPM) model | Proposed (NHD-MPM) model |
|---|---|---|
| PSNR(dB) | 10.8445 | 16.0818 |
| MSE | 13.7461 | 24.9242 |

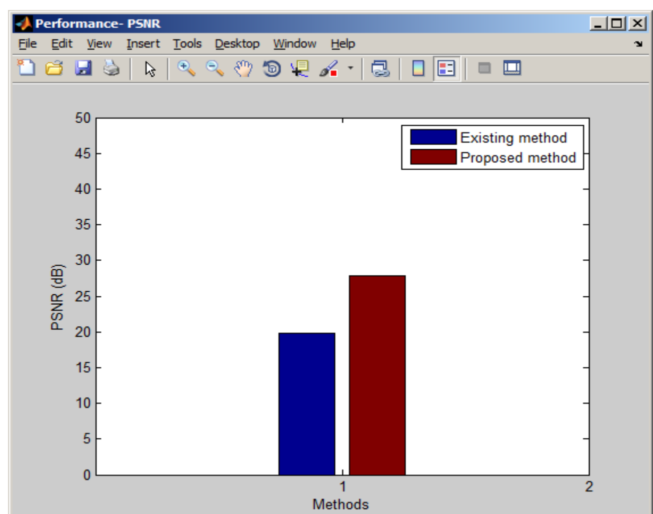


**Figure 14. PSNR comparison results of image denoising methods**

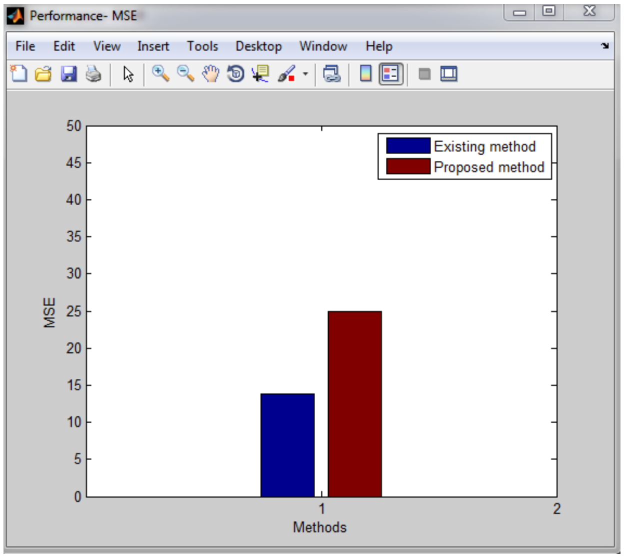


**Figure 15. MSE comparison results of image denoising methods**

Figure 14 shows the PSNR comparison results of the two image denoising methods such as MPM and NHD-MPM model. However the proposed NHD-MPM model produces higher PSNR results of the 10.8445dB whereas the existing MPM method produces only 16.0818 dB. From the results it concludes that the proposed NHD-MPM model produces higher PSNR than the existing MPM model. It concludes that proposed work performs better for removing noises than the other method. Figure 15 shows the MSE comparison results of the two image denoising methods such as MPM and NHD-MPM model. However the proposed NHD-MPM model produces higher MSE results of the 13.7461whereas the existing MPM method produces lesser MSE results of 24.9242. From the results it concludes that the proposed NHD-MPM model produces lesser MSE than the existing MPM model. It concludes that proposed work performs better for removing noises than the other method.

## 5. CONCLUSION AND FUTURE WORK

The aim of this article is to develop a hybrid denoising algorithm based on directional diffusion, via incorporating the advantage of the modified ID model and that of the modified PM model. In the proposed method, employed the patch similarity modulus to serve as the structure indicator to control the diffusion mode and used the second order directional derivative to make the diffusion proceeds along the edge's direction of the original image. First, propose a new edge detection indicator, that is, the diffusivity function. Based on this diffusivity function, the new Nonlinear Hybrid Diffusion is nonlinear anisotropic and forward-backward. A nonlinear hybrid diffusion equation is discussed for image denoising, which is a combination of mean curvature smoothing and Gaussian heat diffusion. Here hybrid image denoising algorithm is based on Nonlinear Hybrid Diffusion - Modified Perona-Malik (NHD-MPM) model. In addition the proposed work parameters of the Nonlinear Hybrid Diffusion are optimized via the use of the Artificial Bee Colony (ABC) optimization. In addition, the patch similarity modulus is used as the new structure indicator for the MPM model. Experimental results illustrate the effectiveness of the new model with respect to other known models. To further validate the performance of the proposed NHD-MPM model, future efforts will be focused toward further optimizing the parameters of the proposed model with hybrid algorithm such that it can be applied to the streak artifacts removal of the low-dose computed tomography (LDCT) images.

## REFERENCES

1. Alvarez L., P.-L. Lions, and J.-M. Morel, "Image selective smoothing and edge detection by nonlinear diffusion. II," SIAM Journal on Numerical Analysis, vol. 29, no. 3, pp. 845–866, 1992.
2. Andreu F., C. Ballester, V. Caselles, and J. M. Mazon, "Minimizing total variation flow," Differential and Integral Equations, vol. 14, no. 3, pp. 321–360, 2001.
3. Atlas, A., Karami, F. and Meskine, D., 2014. The Perona–Malik inequality and application to image denoising. Nonlinear Analysis: Real World Applications, 18, pp.57-68.
4. Babu, A., 2013. Ratio-based Edge Detection Inspired Speckle Reducing Anisotropic Diffusion, thesis , pp.1-104.
5. Barbu, T., Barbu, V., Biga, V. and Coca, D., 2009. A PDE variational approach to image denoising and restoration. Nonlinear Analysis: Real World Applications, 10(3), pp.1351-1361.
6. Caselles V., J.-M. Morel, G. Sapiro, and A. Tannenbaum, "Introduction to the special issue on partial differential equations and geometry-driven diffusion in image processing and analysis," IEEE Transactions on Image Processing, vol. 7, no. 3, pp. 269–273, 1998.
7. Catté, F., Lions, P.L., Morel, J.M. and Coll, T., 1992. Image selective smoothing and edge detection by nonlinear diffusion. SIAM Journal on Numerical analysis, 29(1), pp.182-193.
8. Chao S.-M. and D.-M. Tsai, ``An improved anisotropic diffusion model for detail- and edge-preserving smoothing," Pattern Recognit. Lett., vol. 31, no. 13, pp. 2012_2023, 2010.
9. Charbonnier P., L. Blanc-Feraud, G. Aubert, and M. Barlaud, "Two deterministic half-quadratic regularization algorithms for computed imaging," in Proceedings of IEEE International Conference on Image Processing, vol. 2, pp. 168–172, IEEE Computer Society Press, Austin, Tex, USA, November 1994.

10. Chatterjee, P. and Milanfar, P., 2010. Is denoising dead?. IEEE Transactions on Image Processing, 19(4), pp.895-911.

11. Chen, Y., Shi, L., Feng, Q., Yang, J., Shu, H., Luo, L., Coatrieux, J.L. and Chen, W., 2014. Artifact suppressed dictionary learning for low-dose CT image processing. IEEE transactions on medical imaging, 33(12), pp.2271-2292.

12. Chen, Y., Zhang, Y., Yang, J., Cao, Q., Yang, G., Chen, J., Shu, H., Luo, L., Coatrieux, J.L. and Feng, Q., 2016. Curve-like structure extraction using minimal path propagation with backtracking. IEEE Transactions on image processing, 25(2), pp.988-1003.

13. Iijima T., “Basic theory on normalization of pattern (in case of typical one dimensional pattern),” Bulletin of the Electrotechnical Laboratory, vol. 26, pp. 368–388, 1962 (Japanese).

14. Ji, X., Zhang, D., Guo, Z. and Wu, B., 2013. Image denoising via nonlinear hybrid diffusion. Mathematical Problems in Engineering, 2013, Article ID 890157, pp.1-23.

15. Karami, F., Ziad, L. and Sadik, K., 2017. A splitting algorithm for a novel regularization of Perona-Malik and application to image restoration. EURASIP Journal on Advances in Signal Processing, 2017(1), pp.1-9.

16. Levine, H.A., 1979. AN Tikhonov and VY Arsenin, solutions of ill posed problems. Bulletin (New Series) of the American Mathematical Society, 1(3), pp.521-524.

17. Liu, K., Tan, J. and Ai, L., 2016. Hybrid regularizers-based adaptive anisotropic diffusion for image denoising. SpringerPlus, 5(1), pp-1-24.

18. Loum, G.L., Pandry, G.K., Atiampo, A.K. and Oumtanaga, S., 2017. Hybrid model of diffusion based on the Jeffreys-type equation for noise reduction on images. IET Image Processing, 12(5), pp.716-728.

19. Maulik, R. and San, O., 2016. An explicit relaxation filtering framework based upon Perona-Malik anisotropic diffusion for shock capturing and subgrid scale modeling of Burgers turbulence. arXiv preprint arXiv:1605.04593.

20. Ogada, E.A., Guo, Z. and Wu, B., 2014. An alternative variational framework for image denoising. In Abstract and Applied Analysis ,Vol. 2014, Article ID 939131, pp.1-16.

21. Perona, P. and Malik, J., 1990. Scale-space and edge detection using anisotropic diffusion. IEEE Transactions on pattern analysis and machine intelligence, 12(7), pp.629-639.

22. Prasath, V.S. and Vorotnikov, D., 2014. Weighted and well-balanced anisotropic diffusion scheme for image denoising and restoration. Nonlinear Analysis: Real World Applications, 17, pp.33-46.

23. Romdhane, F., Benzarti, F. and Amiri, H., 2016. Denoising 3D Computed Tomography Images using New Modified Coherence Enhancing Diffusion Model. In VISIGRAPP (3: VISAPP) (pp. 103-107).

24. Rudin, L.I., Osher, S. and Fatemi, E., 1992. Nonlinear total variation based noise removal algorithms. Physica D: nonlinear phenomena, 60(1-4), pp.259-268.

25. Tsiotsios C. and M. Petrou, ``On the choice of the parameters for anisotropic diffusion in image processing," Pattern Recognit., vol. 46, no. 5, pp. 1369-1381, 2013.

26. Wang Y. Q., J. Guo, W. Chen, and W. Zhang, ``Image denoising using modified Perona-Malik model based on directional Laplacian," Signal Process., vol. 93, no. 9, pp. 2548-2558, 2013.

27. Yuan, J. and Wang, J., 2016. Perona–malik model with a new diffusion coefficient for image denoising . International Journal of Image and Graphics, 16(02), pp .1-13.

28. Ziou D. and A. Horé, ``Reducing aliasing in images: A PDE-based diffusion revisited," Pattern Recognit., vol. 45, no. 3, pp. 1180-1194, 2012.