An Effcient Method for Nonlocal Means Image Denoising for Multiple Images using Hybrid Optimization

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Abstract— Noise is always presents in digital images during image acquisition, coding, transmission, and processing steps. Noise is very difficult to remove it from the digital images without the prior knowledge of noise model.Image de-noising refers to the recovery of a digital image that has been contaminated by noise. The presence of noise in images is unavoidable. It may be introduced during image formation, recording or transmission phase. Further processing of the image often requires that the noise must be removed or at least reduced. Even a small amount of noise is harmful when high accuracy is required.During any physical measurement, it is likely that the measured quantity is corrupted by some amount of noise. The sources and types of this noise are depending upon the physical measurement. Noise often comes from a source that is different from the one to be measured, but sometimes it is due to the measurement process itself. In case of images, the example of former one is read-out noise in digital cameras and later one is speckle noise in SAR images. Sometimes, noise might be due to the mathematical manipulation of a signal, as is the case in image de-convolution or image compression. Often, a measurement is corrupted by several sources of noise and it is usually difficult to fully characterize all of them.

In all these cases, noise is the undesirable part of the image. Ideally, one seeks to reduce noise by manipulating the image acquisition process, but when such a manipulation is impossible, de-noising algorithms become mandatory.The proposed work is contributing in two main sections. In the first denoising process, we add a noisy image of which the noise deviation is equal to that of the original noisy image. It can improve the accuracy of finding similar blocks by using the nonlocal property of two images. At the same time, we rule out the smaller weight blocks, thus reduce the interference of un-similar blocks. In the second denoising step, it can further improve the accuracy by using the nonlocal similarity of the residual image. So this paper deals with denoising or enhancement of the image in an effectual manner and the performance is evaluated using mean square error rate and peak signal to noise ratio.

Keywords—*Denoising; ACO; BFO;image noise.*

I. INTRODUCTION

Images are often corrupted with noise during acquisition, transmission, and retrieval from storage media. Many dots can be spotted in a Photograph taken with a digital camera under low lighting conditions. Fig. 1 is an example of such a Photograph. Appereance of dots is due to the real signals getting corrupted by noise (unwanted signals). On loss of reception, random black and white snow-like patterns can be seen on television screens, examples of noise picked up by the television. Noise corrupts both images and videos. The purpose of the denoising algorithm is to remove such noise.Image denoising is needed because a noisy image is not pleasant to view. In addition,some fine details in the image may be confused with the noise or vice-versa. Many image-processing algorithms such as pattern recognition need a clean image to work effectively. Random and uncorrelated noise samples are not compressible. Such concerns underline the importance of denoising in image and video processing.Images are affected by different types of noise.

Fig. 1 (a) Clean Boat Image (b) Noisy Boat Image

A. Image Denoising

Retinal Image denoising refers to the recovery of a digital image that has been contaminated by noise. The presence of noise in images is unavoidable. Image denoising is one of the most essential tasks in image processing for better analysis and vision. There are many types of noise which can decrease the quality of images. The Speckle noise which can be modeled as multiplicative noise mainly occurs in various imaging system due to random variation of the pixel values. It can be defined as the multiplication of random values with the pixel values. Mathematically, this noise is modeled as:

Speckle noise=I*(1+N)

Where 'I' is the original image matrix and 'N' is the noise, which is mainly a normal distribution with mean equal to zero. This noise is a major problem in radar applications. Wiener filtering comes under the non-coherent type of denoising method, which is mainly used as a restoration technique for all type of noisy images [1]. However this filter do not giving promising result in terms of various quality performance measuring indices such as Structural Similarity Index Measure (SSIM), Mean-Square-Error (MSE), Signal-to-Noise Ratio (SNR) and Peak-Signal-to-Noise Ratio (PSNR) between original and restored image. Curvelet transform was introduced by E. J. Candes [2, 3]. It is a higher version of image representation at fine scales, and it is developed from Wavelet as multi-scale representation. In case of image denoising methods, the characteristics of the degrading system and the noises are assumed to be known beforehand. The image s(x,y) is blurred by a linear operation and noise n(x,y) is added to form the degraded image w(x,y). This is convolved with the restoration procedure g(x,y) to produce the restored image z(x,y).

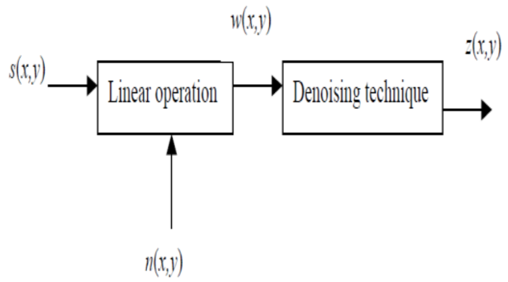

Fig. 2 Denoising concept

The "Linear operation" shown in Fig. 1.1 is the addition or multiplication of the noise n(x,y) to the signal s(x,y) [Im01]. (Once the corrupted image w(x,y) is obtained, it is subjected to the denoising technique to get the denoised image z(x,y).

B. Image Denoising Versus Image Enhancement

Image denoising is different from image enhancement. As Gonzalez and Woods [1]explain, image enhancement is an objective process, whereas image denoising is a subjective process. Image denoising is a restoration process, where attempts are made to recover an image that has been degraded by using prior knowledge of the degradation process. Image enhancement, on the other hand, involves manipulation of the image characteristics to make it more appealing to the human eye. There is some overlap between the two processes.

C. Evolution Of Image Denoising Research

Image De-noising has remained a fundamental problem in the field of image processing. Wavelets give a superior performance in image de-noising due to properties such as sparsity and multi-resolution structure. With Wavelet Transform gaining popularity in the last two decades various algorithms for de-noising in wavelet domain were introduced. The focus was shifted from the Spatial and Fourier domain to the Wavelet transform domain. Ever since Donoho's

Wavelet based thresholding approach was published in 1995, there was a surge in the de-noising papers been 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 de-noising 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 Un-decimated Wavelet Transform [7]. These thresholding techniques were applied to the non-orthogonal wavelet coefficients to reduce artifacts. Multi-wavelets were also used to achieve similar results. Probabilistic models using the statistical properties of the wavelet coefficient seemed to outperform the thresholding techniques and gained ground. Recently, much effort has been devoted to Bayesian de-noising in Wavelet domain. Hidden Markov Models and Gaussian Scale Mixtures have also become popular and more research continues to be published. Tree Structures ordering the wavelet coefficients based on their magnitude, scale and spatial location have been researched. Data adaptive transforms such as Independent Component Analysis (ICA) have been explored for sparse shrinkage. The trend continues to focus on using different statistical models to model the statistical properties of the wavelet coefficients and its neighbors. Future trend will be towards finding more accurate probabilistic models for the distribution of non-orthogonal wavelet coefficients.

II. CLASSIFICATION OF DENOISING ALGORITHMS

A. Noise Sources

The block diagram of a digital camera is shown in Fig. 1.2. A lens focuses the light from regions of interest onto a sensor. The sensor measures the color and light intensity.An analog-to-digital converter (ADC) converts the image to the digital signal. An image-processing block enhances the image and compensates for some of the deficiencies of the other camera blocks. Memory is present to store the image, while a display may be used to preview it. Some blocks exist for the purpose of user control. Noise is added to the image in the lens, sensor, and ADC as well as in the image processing block itself.The sensor is made of millions of tiny light-sensitive components. They differ in their physical, electrical, and optical properties, which adds a signal-independent noise (termed as dark current shot noise) to the acquired image. Another component of shot noise is the photon shot noise. This occurs because the number of photons detected varies across different parts of the sensor. Amplification of sensor signals adds amplification noise, which is Gaussian in nature. The ADC adds thermal as well as quantization noise in the digitization process. The image-processing block amplifies part of the noise and adds its own rounding noise. Rounding noise occurs because there are only a finite number of bits to represent the intermediate floating point results during computations [2].Most denoising algorithms assume zero mean additive white Gaussian noise (AWGN) because it is symmetric, continuous, and has a smooth density distribution. However,many other types of noise exist in practice. Correlated noise with a Gaussian distribution is an example. Noise can also have different distributions such as Poisson, Laplacian, or non-additive Salt-and-Pepper noise. Salt-and-Pepper noise is caused by bit errors in image transmission and retrieval as well as in analog-to-digital converters. A scratch in a picture is also a type of noise. Noise can be signal dependent or signal independent. For example, the process of quantization (dividing a continuous signal into discrete levels)

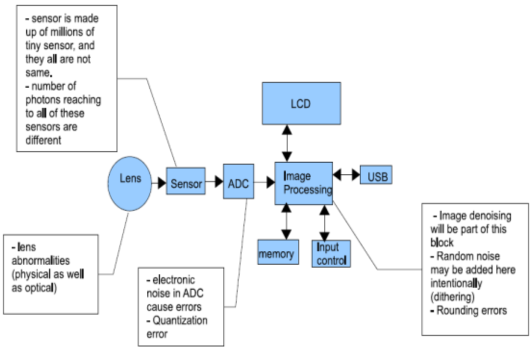

Fig. 3 Basic Blocks of a Digital Camera and Possible Sources of Noiseadds signal-dependent noise.

B. Denoising Artifacts

Denoising often adds its own noise to an image. Some of the noise artifacts created by denoising are as follows:

- Blur: attenuation of high spatial frequencies may result in smoothe edges in the image.Ringing/Gibbs Phenomenon: truncation of high frequency transform coefficients may lead to oscillations along the edges or ringing distortions in the image.
- Staircase Effect: aliasing of high frequency components may lead to stair-like structures in the image.
- Checkerboard Effect: de-noised images may sometimes carry checker board structures.
- Wavelet Outliers: these are distinct repeated wavelet-like structures visible in thede-noised image and occur in algorithms that work in the wavelet domain.

C. Denoising Artifacts

The quality of an image is examined by objective evaluation as well as subjective evaluation. Objective image quality measures play important roles in various image processing applications. Basically there are two types of objective quality or distortion assessment approaches. The first is mathematically defined measures such as Mean Square Error (MSE), Root Mean Square Error (RMSE) and Peak Signal-Noise Ratio (PSNR). The second considers Human Visual System (HVS) characteristics in an attempt to incorporate perceptual quality measures.

III. LITERATURE REVIEW

A. Patel et al. (2016) explained that a fundamental step in image processing is the step of removing various kinds of noise from the image. Sources of noise in an image mostly occur during storage, transmission and acquisition of the image. Image denoising is a applicable issue found in diverse image processing and computer vision problems. There are various existing methods to denoise image. The important property of a good image denoising model is that it should completely remove noise as far as possible as well as preserve edges. The image denosing technique will be mainly depending on the type of the image and noise in cooperating with it. There have been several published algorithms and each approach has its assumptions, advantages and limitations.

X.Wang et al. (2016) proposed that basic principle of non-local means is to denoise a pixel using the weighted average of the neighborhood pixels, while the weight is decided by the similarity of these pixels. The key issue of the non-local means method is how to select similar patches and design the weight of them. There are two main contributions of this paper: The first contribution is that we use two images to denoise the pixel. These two noised images are with the same noise deviation. Instead of using only one image, we calculate the weight from two noised images. After the first denoising process author get a pre-denoised image and a residual image.

A. Buades et al. (2015) has stated that the search for efficient image denoising methods still is a valid challenge, at the crossing of functional analysis and statistics. In spite of the sophistication of the recently proposed methods most algorithms have not yet attained a desirable level of applicability. All show an outstanding performance when the image model corresponds to the algorithm assumptions, but fail in general and create artifacts or remove image fine structures. The author defined a general mathematical and experimental methodology to compare and classify classical image denoising algorithms, second to propose an algorithm (Non Local Means) addressing the preservation of structure in a digital image. The mathematical analysis is based on the analysis of the “method noise”, defined as the difference between a digital image and its denoised version. The NL-means algorithm is also proven to be asymptotically optimal under a generic statistical image model.

J. patil et al. (2015) has described that visual information transmitted in the form of digital images is becoming a major method of communication in the modern age but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image denoising involves the manipulation of the image data to produce a visually high quality image. The author has reviewed that the Noise models, Noise types and classification of image denoising techniques. The author presented a comparative analysis of various noise suppression algorithms.

S. Kaur et al. (2014) has mentioned the main challenge in digital image processing is to remove noise from the original image. The author has reviewed the existing denoising algorithms and performs their comparative study. Different noise models including additive and multiplicative types are discussed. Selection of the denoising algorithm is application dependent. Hence it is necessary to have knowledge about the noise present in the image so as to select the appropriate denoising algorithm. Author puts results of different approaches of wavelet based image denoising methods using several thresholding techniques such as Bayes Shrink, Sure Shrink and Visu Shrink. A quantitative measure of comparison is provided by SNR (signal to noise ratio) and mean square error (MSE).

S. shreshtha et al. (2014) stated that noise is a major issue while transferring images through all kinds of electronic communication. One of the most common noise in electronic communication is an impulse noise which is caused by unstable voltage. The author described the comparison of known image denoising techniques and a new technique using the decision based approach has been used for the removal of impulse noise. All these methods can primarily preserve image details while suppressing impulsive noise. The principle of these techniques is at first introduced and then analysed with various simulation results using MATLAB. Most of the previously known techniques are applicable for the denoising of images corrupted with less noise density. Here a new decision based technique has been presented which shows better performances than those already being used. The comparisons are made based on visual appreciation and further quantitatively by Mean Square error (MSE) and Peak Signal to Noise Ratio (PSNR) of different filtered images.

J. Caia et al. (2013) introduced Sparsity based regularization methods for image restoration assume that the underlying image has a good sparse approximation under a certain system. Such a system can be a basis, a frame or a general over-complete dictionary. One widely used class of such systems in image restoration are wavelet tight frames. There have been enduring efforts on seeking wavelet tight frames under which a certain class of functions or images can have a good sparse approximation. However the structure of images varies greatly in practice and a system working well for one type of images may not work for another. The author presented a method that derives a discrete tight frame system from the input image itself to provide a better sparse approximation to the input image. Such an adaptive tight frame construction scheme is applied to image denoising by constructing a tight frame tailored to the given noisy data.

M. kaur et al. (2013) has proposed an adaptive threshold estimation method for image denoising in the wavelet domain based on the generalized Gaussian distribution (GGD) modeling of sub band coefficients. The proposed method called Normal Shrink is computationally more efficient and adaptive because the parameters required for estimating the threshold depend on sub band data. The threshold is computed by βσ 2 / σy where σ and σy are the standard deviation of the noise and the sub band data of noisy image respectively. β is the scale parameter which depends upon the sub band size and number of decompositions. Experimental results on several test image are compared with various denoising techniques like wiener Filtering.

R. ahmadi et al. (2013) discussed image denoising called as a mean filter that acts on an image by smoothing it.It reduces the intensity variation between adjacent pixels. The mean filter is nothing but a simple sliding window spatial filter that replaces the center value in the window with the average of all the neighboring pixel values including itself. Image corrupted with salt and pepper noise is subjected to mean filtering and it can be observed that the noise dominating is reduced.

T.L. Sahu et al. (2012) stated that digital images are noisy due to environmental disturbances. To ensure image quality image processing of noise reduction is a very important step before analysis or using images. Data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process and interfering with natural phenomena can all degrade the data of interest. The importance of the image denoising could be a serious task for medical imaging, satellite and a real image processing robot vision, industrial vision systems, micro vision systems, space exploring etc.

S. Ruikar et al. (2011) proposed different approaches of wavelet based image denoising methods. The search for efficient image denoising methods is still a valid challenge at the crossing of functional analysis and statistics. In spite of the sophistication of the recently proposed methods, most algorithms have not yet attained a desirable level of applicability. Wavelet algorithms are useful tool for signal processing such as image compression and denoising. Multi wavelets can be considered as an extension of scalar wavelets. The main aim is to modify the wavelet coefficients in the new basis, the noise can be removed from the data. The author extended the existing technique and providing a comprehensive evaluation of the proposed method. Results based on different noise, such as Gaussian, Poisson's, Salt and Pepper and Speckle performed signal to noise ratio as a measure of the quality of denoising was preferred.

L. Yan et al. (2011) has used the noisy chaotic neural network (NCNN) that has proposed earlier for image denoising as a constrained optimization problem. The experimental results show that the NCNN is able to offer good quality solutions.

V. Laparra et al. (2010) explained a successful class of image denoising methods is based on Bayesian approaches working on wavelet representations. The performance of these methods improves when relations among the local frequency coefficients are explicitly included. However in these techniques analytical estimates can be obtained only for particular combinations of analytical models of signal and noise thus precluding its straightforward extension to deal with other arbitrary noise sources. The author proposed an alternative non-explicit way to take into account the relations among natural image wavelet coefficients for denoising, use of support vector regression (SVR) in the wavelet domain to enforce these relations in the estimated signal. Since relations among the coefficients are specific to the signal, the regularization property of SVR is exploited to remove the noise which does not share this feature.

F. Palhano et al. (2010) explained that image denoising is the process of removing the noise that perturbs image analysis methods. In some applications like segmentation or registration denoising is intended to smooth homogeneous areas while preserving the contours. In many applications like video analysis, visual serving or image-guided surgical interventions, real-time denoising is required. The author presented a method for real-time denoising of ultrasound images: a modified version of the NL-means method is presented that incorporates an ultrasound dedicated noise model as well as a GPU implementation of the algorithm. Results demonstrate that the proposed method is very efficient in terms of denoising quality and is real-time.

S. Kumar et al. (2010) described spatial filtering methods for image denoising in which the Median Filter is performed by taking the magnitude of all of the vectors within a mask and sorted according to the magnitudes. The pixel with the median magnitude is then used to replace the pixel studied. The Simple Median Filter has an advantage over the Mean filter since median of the data is taken instead of the mean of an image. The pixel with the median magnitude is then used to replace the pixel studied. The median of a set is more robust with respect to the presence of noise.

K. Dabov et al. (2007) proposed a novel image denoising strategy based on an enhanced sparse representation in transform domain. The enhancement of the sparsity is achieved by grouping similar 2-D image fragments into 3-D data arrays which we call “groups.” Collaborative filtering is a special procedure developed to deal with these 3-D groups. The author has released it using the three successive steps: 3-D transformation of a group, shrinkage of the transform spectrum and inverse 3-D transformation. The result is a 3-D estimate that consists of the jointly filtered grouped image blocks.

H. Guo et al. (2007) introduced coefficient model for image denoising that focuses on exploiting the multi-resolution properties of Wavelet Transform. This technique identifies a close correlation of signal at different resolutions by observing the signal across multiple resolutions. This method produces excellent output but is computationally much more complex and expensive. The modeling of the wavelet coefficients can either be deterministic or statistical.

A. Pizurica et al. (2006) has developed the three novel wavelet domain denoising methods for sub band-adaptive, spatially-adaptive and multivalued image denoising. The core of our approach is the estimation of the probability that a given coefficient contains a significant noise-free component, which is called “signal of interest”. In this respect author analyze cases where the probability of signal presences (i) fixed per sub band (ii) conditioned on a local spatial context and (iii) conditioned on information from multiple image bands. All the probabilities are estimated assuming a generalized Laplacian prior for noise-free data and additive white Gaussian noise. The performance on color and on multi spectral image is superior with respect to recent multiband wavelet thresholding.

M. Mutwani et al. (2005) discussed that removing noise from the original signal is still a challenging problem for researchers. There have been several published algorithms and each approach has its assumptions, advantages and limitations. The author presented a review of some significant work in the area of image denoising. After a brief introduction some popular approaches are classified into different groups and an overview of various algorithms and analysis is provided. Insights and potential future trends in the area of denoising are also discussed.

K. Mohan et al. (2004) introduced a Spatial-frequency filtering that is referred to use of low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods the removal of the noise is achieved by designing a frequency domain filter and adapting a cut-off frequency when the noise components are relocated from the useful signal in the frequency domain. These methods are time consuming and depend on the cut-off frequency and the filter function behavior. Furthermore, they may produce artificial frequencies in the processed image.

M. Kazubek et al. (2003) described the Wiener filter method for image denoising that is used to filter out noise that has corrupted a signal. It is based on a statistical approach. Typical filters are designed for a desired frequency response. The Wiener filter approaches filtering from a different angle. One is assumed to have knowledge of the spectral properties of the original signal and the noise and one seeks the LTI filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following assumption: signal and (additive) noise are stationary linear random processes with known spectral characteristics and Requirement: the filter must be physically realizable, i.e. causal that means this requirement can be dropped, resulting in a non-causal solution.

S. Dangeti et al. (2003) stated that visual information transmitted in the form of digital images is becoming a major method of communication in the modern age but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image denoising involves the manipulation of the image data to produce a visually high quality image. The author has reviewed that the existing denoising algorithms such as filtering approach wavelet based approach and multifractal approach and performs their comparative study. Different noise models including additive and multiplicative types are used. They include Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. Selection of the denoising algorithm is application dependent. Hence it is necessary to have knowledge about the noise present in the image so as to select the appropriate denoising algorithm.

L. Sendur et al. (2002) described that the performance of image denoising algorithms using wavelet transforms can be improved significantly by taking into account the statistical dependencies among wavelet coefficients as demonstrated by several algorithms presented in the literature. A simple bivariate shrinkage rule is described using a coefficient and its parent. The performance can also be improved using simple models by estimating model parameters in a local neighborhood. This letter presents a locally adaptive denoising algorithm using the bivariate shrinkage function. The algorithm is illustrated using both the orthogonal and dual tree complex wavelet transforms.

IV. RESEARCH PROBLEM FORMULATIONS

Denoising and Enhancement is the very crucial process while developing screening systems, since image serve as one of the main innovative feature in real time applications.Prior works on image denoising can be mainly separated into three categories:

1) Window based,

2) Classifier based

3) Tracking based.

Image denoising and examination of the various images is very time consuming and are independent tasks and as the number of images increases, the computations and complexity also increases rapidly.In the practical imaging system, there exist different kinds of noise. These noises increases the complexity as the pixels got disturbed which degrades the performance of the system. In image denoising, an image is often divided into many small patches which are repeatedly appearing. We can remove the noise by taking advantages of the redundant information of patches while preserving the slight structure of images at the same time.

The proposed work is contributing in two main sections. In the first denoising process, we add a noisy image of which the noise deviation is equal to that of the original noisy image. It can improve the accuracy of finding similar blocks by using the nonlocal property of two images. At the same time, we rule out the smaller weight blocks, thus reduce the interference of unsimilar blocks. In the second denoising step, it can further improve the accuracy by using the nonlocal similarity of the residual image.So the proposed approach deals with denoising or enhancement of the image in an effectual manner and the performance is evaluated using mean square error rate and peak signal to noise ratio.

A. objectives

The basic principle of nonlocal means is to denoise a pixel using the weighted average of the neighborhood pixels, while the weight is decided by the similarity of these pixels. The key issue of the nonlocal means method is how to select similar patches and design the weight of them. The objectives of the research work are:

1. To study the concept of image denoising using image processing

2. To Implement the nonlocal means approach in noisy environment for the similarity calculation

3. To optimize the results of the image denoising using proposed hybrid optimization approach(ant colony optimization and bacterial foraging optimization).

4. To compare the analysis the proposed work on the basis of various parameters such as: mean square error rate and peak signal to noise ratio for image denoising.

V. RESULTS AND DISCUSSION

Image de-noising is typically the process of optimizing the image and extracting the useful objects from the image. It is commonly performed by subtraction the useless objects from the image. The useful object location is calculated by using various techniques like edge detection and some morphological operations and filters. However these techniques suffer from various types of noises like Gaussian noise, sand noise etc. An image is nothing more than a two dimensional signal. It is defined by the mathematical function f(x,y) where x and y are the two co-ordinates horizontally and vertically. The value of f(x,y) at any point is gives the pixel value at that point of an image. Practical application of image segmentation range of content-based image retrieval, medical imaging, and recognition tasks etc. The diversity in segmentation types has led to the wide range of approaches for image segmentation. Below Fig. shows the components of taken in the coordinated plane. As there are lot of interferences from various objects which deals with the distortion of the image and its degradation of the performance, So we have to perform the optimization approach which deals with the high enhancement of the image.

A. Algorithms Used In The Proposed Work

1) Ant Colony optimization: The ant colony optimization algorithm is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. Artificial Ants stand for multi-agent methods inspired by the behavior of real ants. The pheromone-based communication of biological ants is often the predominant paradigm used. Combinations of Artificial Ants and local search algorithms have become a method of choice for numerous optimization tasks involving some sort of graph, e. g., vehicle routing and internet routing. The burgeoning activity in this field has led to conferences dedicated solely to Artificial Ants, and to numerous commercial applications by specialized companies such as Ant-Optima. As an example, Ant colony optimization is a class of optimization algorithms modeled on the actions of an ant colony. Artificial 'ants' (e.g. simulation agents) locate optimal solutions by moving through a parameter space representing all possible solutions. Real ants lay down pheromones directing each other to resources while exploring their environment. The simulated 'ants' similarly record their positions and the quality of their solutions, so that in later simulation iterations more ants locate better solutions. One variation on this approach is the bees algorithm, which is more analogous to the foraging patterns of the honey bee, another social insect.In the natural world, ants of some species (initially) wander randomly, and upon finding food return to their colony while laying down pheromone trails. If other ants find such a path, they are likely not to keep travelling at random, but instead to follow the trail, returning and reinforcing it if they eventually find food (see Ant communication). Over time, however, the pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate. A short path, by comparison, gets marched over more frequently, and thus the pheromone density becomes higher on shorter paths than longer ones. Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained. The influence of pheromone evaporation in real ant systems is unclear, but it is very important in artificial systems. The overall result is that when one ant finds a good path from the colony to a food source, other ants are more likely to follow that path, and positive feedback eventually leads to many ants following a single path. The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph representing the problem to solve.

2) Bee Colony optimization: The Bacterial Foraging Optimization Algorithm belongs to the field of Bacteria Optimization Algorithms and Swarm Optimization, and more broadly to the fields of Computational Intelligence and Met heuristics. It is related to other Bacteria Optimization Algorithms such as the Bacteria Chemotaxis Algorithm and other Swarm Intelligence algorithms such as Ant Colony Optimization and Particle Swarm Optimization. There have been many extensions of the approach that attempt to hybridize the algorithm with other Computational Intelligence algorithms and Met heuristics such as Particle Swarm Optimization, Genetic Algorithm, and Tabu Search. Bacteria perceive the direction to food based on the gradients of chemicals in their environment. Similarly, bacteria secrete attracting and repelling chemicals into the environment and can perceive each other in a similar way. Using locomotion mechanisms (such as flagella) bacteria can move around in their environment, sometimes moving chaotically (tumbling and spinning), and other times moving in a directed manner that may be referred to as swimming. Bacterial cells are treated like agents in an environment, using their perception of food and other cells as motivation to move, and stochastic tumbling and swimming like movement to re-locate. Depending on the cell-cell interactions, cells may swarm a food source, and/or may aggressively repel or ignore each other.

The results of the proposed approach are discussed below which are the solutions of the proposed implemented techniques.

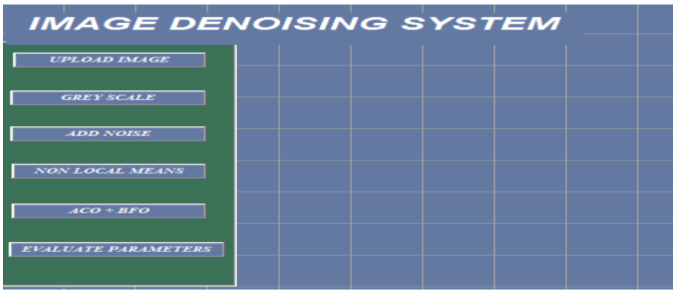

Fig. 4 Original Panel

The above Fig. shows the user interface controls which deals with the uploading and processing of the uploaded samples of the image and shows that the user interface controls are more useful for the effectual processing of the image in the de-noising process.

Fig. 5 Original and grey scale image

The proposed approach shows the original uploading sample and grey scale of the image which deals with after the clicking on the uploaded image.

Fig. 6 Noisy Image

The Fig. 6 shows the noisy image which deals with the distortions in the image and it shows that the proposed system consists of the noisy sample of the uploaded image.

Fig. 7 De-Noise Image using Non local means and optimization

The above Fig. shows the de-noising of the image of the proposed approach which deals with the enhancement and removal of the noise in the image which results in the de-noising process. As we can see the above sample that the proposed hybrid approach is able to achieve high de-noising of the image which shows the cleared image sample after removing the distortions of the image.

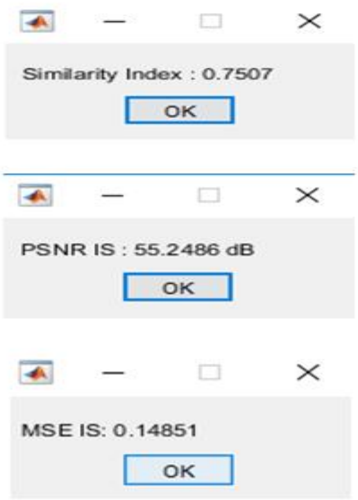

Fig. 8 Performance Evaluation

The above Fig. shows the performance evaluation of the image which deals with the high means square error rate, peak signal to noise ratio and similarity index. The peak signal to noise ratio must be high and mean square error rate must be low for the appropriate similarity index. The similarity index must be high for the high similarity index for the high de-noising image.

TABLE I Performance Evaluation

Parameters	**Proposed**
Peak Signal to noise Ratio	55.28
Mean Square Error Rate	0.148
Similarity Index	0.7507

TABLE II Performance Comparison

Parameters	**Proposed**	**Base**
Peak Signal to noise Ratio (db)	55.28	35.3

The above output table shows the performance analysis on the basis of various parameters. The table 4.1 shows the outcomes on the basis of peak signal to noise ratio, Mean square error rate and similarity index. The proposed work shows the better results in terms of all the parameters. The table 4.2 shows the comparative analysis of the existing and proposed work. The outcomes of the peak signal to noise ratio shows the better result in the proposed system as compared with the existing system.

CONCLUSION

Retinal Image denoising is an applicable issue found in diverse image processing and computer vision problems. There are various existing methods to denoise image. The important property of a good image denoising model is that it should completely remove noise as far as possible as well as preserve edges. Image Denoising has remained a fundamental problem in the field of image processing. Due to properties like sparsity and multi resolution structure, Wavelet transform have become an attractive and efficient tool in image denoising. With Wavelet Transform gaining popularity in the last two decades various algorithms for denoising in Wavelet Domain were introduced. Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensate for distortion in the optical system of a telescope. Image denoising finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality. The proposed work was contributing in two main sections. In the first denoising process, we added a noisy image of which the noise deviation was equal to that of the original noisy image. It can improve the accuracy of finding similar blocks by using the nonlocal property of two images. At the same time, we also rule out the smaller weight blocks, thus reduce the interference of un-similar blocks. In the second denoising step, it can further improve the accuracy by using the nonlocal similarity of the residual image. So the proposed approach deals with denoising or enhancement of the image in an effectual manner and the performance has also been evaluated using mean square error rate and peak signal to noise ratio.

As future research, we would like to work further on the comparison of the denoising techniques. The current research work indicates the ability of the proposed de-noising method. However, further investigations may improve the recovered images under multiplicative noise condition. During the research work a few directions for further research have been identified. These are stated below:

- Exploring various thresholding techniques in sparse domain.
- Developing restoration technique in real-time embedded platform.
- The latest optimization can also apply to improve the results..

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