Journal of Engineering and Applied Sciences 15 (7): 1743-1758, 2020
ISSN: 1816-949X

An Adaptive Image Denoising Model Based on Rank-Ordered Logarithmic Difference and Niching Genetic Algorithm

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Abstract: The denoising methods are an important subsystem of any signal processing system used for image enhancement because these methods remove undesirable signal components from the signal of interest. Noise suppression can introduce artefacts or cause image blurring which makes image denoising a complex task. Several image denoising approaches have been investigated in the literature; however, removing noise from images is still a challenging problem as it designed only for a convinced kind of noise and image or requires statistical properties of the corrupting noise. The aim of this research is to propose an optimal image denoising model using niching genetic algorithm by taking into consideration the most discriminative descriptors (features for uncorrupted and corrupted pixels) which can greatly improve the model performance. The suggested model demonstrates that suitable use of Rank-Ordered Logarithmic Difference (ROLD) can play a key role in determining more noisy pixels with less false hits. ROLD serves as an important definition of pixels and distinguishes between noise pixels and normal pixels (noise and normal pixels signature). Based on some statistical measurements of uncorrupted group of pixels, niching GA is utilized to smooth the corrupted pixels depending on PSNR fitness function between the associated group of pixels. In the suggested system, clearing based niching procedure is adapted to force the GA to maintain a heterogeneous population throughout the evolutionary process, thus, avoiding the convergence to a single optimum. Niching method has been employed to minimize the effect of genetic drift resulting from the selection operator in the traditional GA in order to allow the parallel investigation of many solutions in the population. Experimental results indicate that proposed model has a better performance on PSNR and a stronger capacity of preserving the details than previous denoising techniques.

Key words: Image denoising, ROLD, niching genetic algorithm, bio-inspired image enhancement, population, discriminative

INTRODUCTION

The aim of digital image processing is to improve the potential information for human interpretation and processing of image data for storage, transmission and representation for autonomous machine perception (Ramesh, 2012). The quality of image degrades due to contamination of various types of noises that corrupt an image during the processes of acquisition, transmission, reception, storage and retrieval. For a meaningful and useful processing such as image segmentation and object recognition and to have very good visual display in applications like television, photo-phone, the acquired image signal must be noise-free and made denoising. In the present research work, efforts are made to suggest efficient algorithm that suppress the noise and preserve the edges and fine details of an image as far as possible in wide range of noise density.

The problem of image denoising can be mathematically presented as Y = X+N where Y is the observed noisy image, X is the original image and N is the Noise. The objective is to estimate X given Y: $\hat{X}$ = E [X|Y]. The dif culty lies in determining the probability density function ρ (X|Y) (Anchal *et al*., 2018). During the past decade, numerous denoising methods have been suggested to this end that includes spatial filtering methods, transform based methods and techniques based on the solution of partial differential equations. There are various factors which need to be considered in selecting a noise reduction algorithm. They are the available computer power and time, whether sacrificing some real detail is acceptable if it allows more noise to be removed and the characteristics of the noise.

The methods only exploit the spatial redundancy in a local neighborhood are referred to as local methods. Recently, a number of non-local methods have been developed. These methods estimate every pixel intensity based on information from the whole image, thereby exploiting the presence of similar patterns

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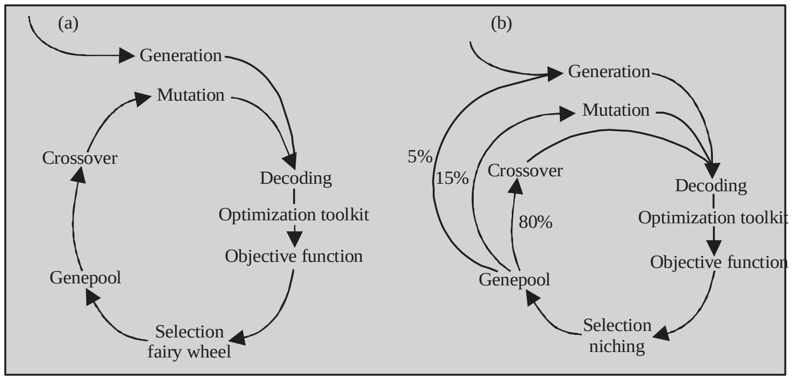

Fig. 1 (a, b): (a) Classical genetic algorithm and (b) Genetic algorithm with niching

and features in an image. Basically, the non-local filter estimates a noise-free pixel intensity as a weighted average of all pixel intensities in the image and the weights are proportional to the similarity between the local neighborhood of the pixel being processed and local neighborhoods of surrounding pixels (Gupta and Negi, 2013).

Noise suppression can introduce artefacts or cause image distorting which makes image denoising a difficult job. Several attitudes have been suggested to eliminate noise in digital images, however, each one explores specific traits of the problem (Akrem and Saleh, 2018). The existing methods have many limitation as it designed only for a convinced kind of noise and image or require statistical properties of the corrupting noise (Nitika, 2017). Also in directive to obtain the best results all entail tedious manual parameterizations and a prior knowledge are neccecery. Furthermore, all denoising methods assume some underlying image regularity.

There are two basic approaches to image denoising, spatial filtering methods and transform domain filtering domain methods (Gupta and Gupta, 2013). A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters. With non-linear filters, the noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible. In recent years, a variety of nonlinear median type filters (such as weighted median) have been developed to overcome this drawback. The transform domain based 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. Transform domain filtering is more appropriate if no straight forward or simple mask can be found in spatial domain (Judith and Kumarasabapathy, 2011; Arivazhagan *et al*., 2007; Rajni and Anutam, 2014). Recently, the incorporation of specialized Genetic Algorithms (GA) in the noise reduction has received a great deal of attention among researchers working in this field (Ram *et al*., 2011; Rakesh and Saini, 2012; Ruikar and Doye, 2011; Sethunadh and Tessamma, 2013). Niching methods are robust optimization techniques which allow multiple solutions in multimodal domains to be found. They can be easily coupled with GAs with only a small increase of the computational time resulting from the computation of the distances between individuals. Nevertheless, this drawback is minor in relation to the advantages of these methods Fig. 1 shows a comparison of the classical genetic algorithm with the applied method of niching. Niching Genetic algorithms differ in the selection process where for each offspring; the chromosome with the smallest hamming-distance (least number of different bits) is located and selected if its fitness is worse than that of the offspring. Whereas in the classical genetic algorithm the whole population is subject to a fitness ranking, the selection in the niching genetic algorithm is performed on the level of each individual (Mohideen *et al*., 2008; Preethi and Narmadha, 2012).

Motivation and problem statement: Image denoising is used to produce improved estimates of an image corrupted by noise due to a noisy sensor or channel transmission errors. A good and effective denoising technique should not result in smoothing the edges of the original image but the removal of noise without blurring the image edges is a difficult task. Motivated by the challenges that are facing image denoising techniques based on genetic algorithm to determine the optimal weights of the average pixels level and in order to cope with them in this study, a modified approach for detection and reduction of image noise was introduced based on niching genetic algorithm by promoting the formation of stable sub-populations in the neighbourhood of optimal solutions to find more than one local optimum.

Contribution: The aim of this research is to propose an optimal image denoising model using niching genetic algorithm by taking into consideration the most discriminative descriptors. The suggested model utilizes Rank-Ordered Logarithmic Difference (ROLD) to determine noisy pixels with less false hits. To resolve the issues related to preserving the smoothing the edges of the original image after denoising process, NGA is utilized in which a population of noisy pixels is evolved for several epochs applying tailor-made crossover and mutation operators. In the suggested system, clearing-based niching procedure is adapted to force the GA to maintain a heterogeneous population throughout the evolutionary process, thus, avoiding the convergence to a single optimum. These mechanisms allow the GA to identify, along with the global optimum, the local optima in a multimodal domain. Niching method has been employed to minimize the effect of genetic drift resulting from the selection operator in the traditional GA in order to allow the parallel investigation of many solutions in the population. The suggested model addresses the drawbacks of existing methods, especially, the miss detection of noise-free pixels as noisy pixels and vice versa.

Literature review: In the study of they proposed a method that can optimize the parameters of Pulse Coupled Neural Network (PCNN) by joining the Genetic Algorithm (GA) and ant colony algorithm which named as GACA and the optimized technique is named as GACAPCNN. Firstly, the noisy image is clarified by median filter in the proposed GACA-PCNN method, after that the noisy image is clarified by GACA-PCNN regularly and the median filtering image is used as a reference image, finally, a set of parameters of PCNN can be automatically assessed by GACA and the pretty effective denoising image will be obtained. Experimental results showed that GACA-PCNN has in term of PSNR (peak signal noise rate), the quality of the image shows a great improvement compared to other conventional denoising methods, i.e., AD filter, Wiener filter, mean filter, median filter and COR-PCNN. And the advantage of this method that it has a stronger capability of maintaining the details.

A new segmentation algorithm of brain MRI image was studied by which uses the noise reduction method with adaptive dictionary based on genetic algorithm and the experimental results showed that the algorithm in brain MRI image separation has fast calculation speed and the advantage of precise subdivision, also in a very complex condition, the results showed that the segmentation of brain MRI images can be accomplished effectively by exhausting this algorithm and it accomplishes the ideal effect and has good exactitude. Also the advantage of the proposed algorithm has higher stability, more accurate segmentation, also greatly reduces the computational complexity of genetic algorithm. This algorithm has better portability in practical applications and is easier to popularize.

The researchers by Saraiva *et al*. (2018), refers to a new model of genetic algorithm. The method used has finality of optimize the filtering of artifacts in DICOM images in two-steps. The first step is constituted by filterings with BM4D, 3D median filter and ellipsoid filter. The second step is formed by the application of operators of simple mutations in the previously recovered image, for that was used: intensity change, gaussian filter and mean filter. As a result, a better performance filter was obtained and which provides an improvement in diagnosis in diseases assessment and in decisions making by the professional. The advantage it was observed experimentally that the adopted filter is efficient and robust presenting indexes better than the others in the PSNR and SSIM. With the study of the HGA3D can generate more advances and minimize the artifacts, resulting in a better performance in the system. The disadvantage is the limitations of techniques for the random values, that make it difficult the optimal value defined in the filtering in order to apply more efficient methods of reconstruction of DICOM images, it is intended in future works to approach the methods with the application of new filters to increase efficiency.

Image analysis involves processing and extraction of knowledge from images which is significantly useful in the large scale of medical and engineering applications. Image denoising is primarily applied in image analysis for degradation of noise and thus improves the visual quality of images for information retrieval process. In the recent scenarios, due to the increase of complexity and diversity of digital images, removal of noise present in complicated images using classical filters becomes a quite challenge. the researchers by Dhivyaprabha *et al*. (2018) investigate the performance efficiency of a newly developed Synergistic Fibroblast Optimization based Weighted Median Filter (SFO-WMF) for medical image analysis. Experiments are carried out with benchmark images, real time Magnetic Resonance Imaging (MRI) images, ultrasound breast cancer images and compared with conventional filters, namely, mean filter, median filter, wiener filter, Gaussian filter and weighted median filter. The performances of filters are validated using standard performance metrics and computational results demonstrated that the novel filter produces promising results and it outperforms than conventional filters in both qualitative and quantitative perspectives. The advantage of this method is could be well suited for diverse sort of medical image processing applications and analysis.

The researcher by discussed different filtering techniques for removing noises in color image. Furthermore, they presented and compared results for these filtering techniques. The results obtained using median filter technique ensures noise free and quality of the image as well. The main advantages of this medium filter are the denoising capability of the destroyed color component differences. Hence, the method can be suitable for other filters available at present. But this technique increases the computational complexity the construction of feed-forward Denoising Convolutional Neural Networks (DnCNNs) to embrace the progress in very deep architecture, learning algorithm and regularization method into image denoising was introduced in the study of Zhang *et al*. (2017) in which Specifically, residual learning and batch normalization are utilized to speed up the training process as well as boost the denoising performance. Different from the existing discriminative denoising models which usually train a specific model for Additive White Gaussian Noise (AWGN) at a certain noise level, the DnCNN Model is able to handle Gaussian denoising with unknown noise level (i.e., blind Gaussian denoising). With the residual learning strategy, DnCNN implicitly removes the latent clean image in the hidden layers. This property motivates to train a single DnCNN Model to tackle with several general image denoising tasks such as Gaussian denoising, single image super-resolution and JPEG image deblocking. The advantage of DnCNN model can not only exhibit high effectiveness in several general image denoising tasksbut also be efficiently implemented by benefiting from GPU computing and the proposed method not only produces favorable image denoising performance quantitatively and qualitatively but also has promising run time by GPU implementation. Disadvantage that the CNN models not tested for denoising of images with real complex noise and other general image restoration tasks.

An optimum threshold detection scheme based on genetic algorithm for image denoising can be found by Pramitha and Anil (2017) and it has been mentioned that the denoising algorithm is selected related to the type of application used. The high frequency analysis techniques like Non Harmonic Analysis (NHA) based denoising methods are currently used in image processing. They have good noise removal accuracy. But choice of threshold is a major drawback of such methods. Optimum threshold value was detected using the genetic algorithm. Thus, denoising quality was improved. Also it gives good edge preservation results.

In the study of a efficient adaptive method based on MDBPTGMF algorithm which perform better in restoring gray scale as well as color images corrupted by salt and pepper noise. The experimental results show that the adaptive algorithm gives better result in terms of PSNR and IEF values as compare to other existing algorithms. As in the proposed method, the noise is detected by comparing the pixels of image directly with 0 or 255 value, therefore, it has no detection error, works for gray scale images and color images as well as it performs well for all image formats. Li provided an updated survey on niching methods. The work first revisits the vital ideas about niching and its most descriptive schemes, then reviews the more recent development of niching methods including novel and hybrid methods, presentation measures and levels for their valuation. Moreover, the work surveys previous attempts on leveraging the capabilities of niching to facilitate various optimization (e.g., multi-objective and dynamic optimization) and machine learning (e.g., clustering, feature selection and learning ensembles) tasks. A list of successful applications of niching methods to real-world problems is provided to validate that niching methods are able to provide solutions that are difficult for conventional optimization methods to offer. The significant practical value of niching methods is clearly demonstrated through these applications. Finally, they poses challenges and research questions on niching that are yet to be appropriately addressed. Providing answers to these questions is crucial before it can bring more fruitful benefits of niching to real-world problem solving.

According to the aforementioned review, it can be found that past studies were primarily devoted to: those that use filtering or transforming methods: such methods mainly use spatially and transform domain filter. Denoising performance of these filters is measured using the quantitative performance measures such as Signal-to Noise Ratio (SNR) and Peak Signal-to-Noise Ratio (PSNR) as well as visual quality of images. Those that use optimization method like genetic algorithms, niching Genetic algorithms.

Finally, there are machine learning methods that can be applied to the image noise reduction such as neural networks and fuzzy. Because the selection of denoising technique depends on what kind of denoising is required. Further, it depends on what kind of information is required. Few examples, fuzzy model will be a good choice to represent the region boundaries ambiguity. Numerous research on denoising methods are scheduled below.

MATERIALS AND METHODS

Problem formulation: In all real applications, measurements are perturbed by noise. In the course of acquiring, transmitting or processing a digital image for example, the noise-induced degradation may be dependent on or independent of data. Efficient suppression of noise in an image is a very important issue.

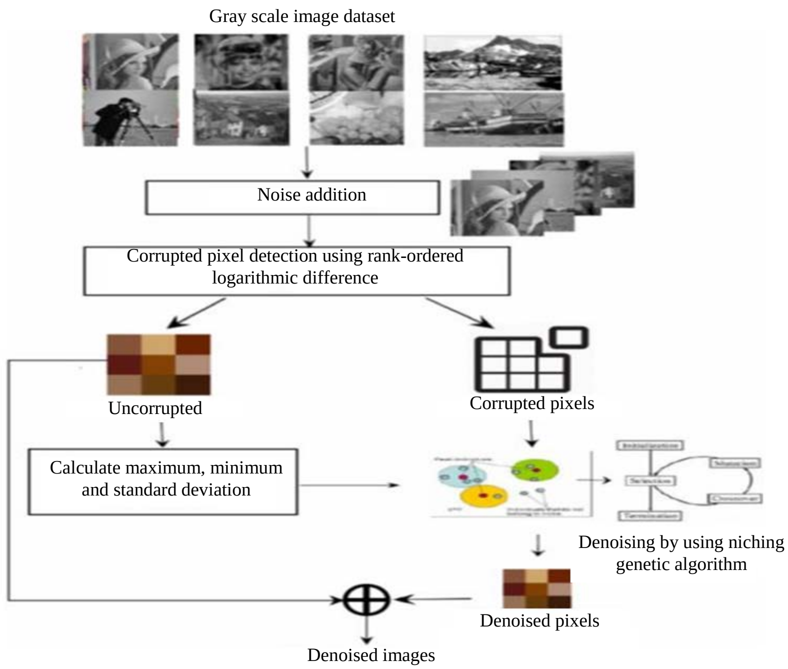

Fig. 2: Proposed image denoising model based on niching Genetic algorithm

Denoising finds extensive applications in many fields of image processing. Image denoising is an important pre-processing task before further processing of image like segmentation, feature extraction, texture analysis etc. The purpose of denoising is to remove the noise while retaining the edges and other detailed features as much as possible (Fig. 2).

Tested image: The image included in this study was taken from the grayscale image dataset (available at: https://(homepages.cae.wisc.edu/~ece533/images/) and divided according to their dimension size, type. Many kinds of noise can exist in images as a result of applying different procedures on them like compression, data transmission and acquisition etc.

Addition of noise: The included images was corrupted with different type of noise (Gaussian, Salt and pepper, Speckle and Poisson) which added by MATLAB program at different density to determine the efficiency of the proposed system. And according to the equation formula that specific for each type as mentioned previously in chapter two.

Noise detection: A range of noisy pixel in an input acquired image was estimated in which the uncorrupted pixels may lie. The pixels which not lie in an estimated range are detected as noisy or corrupted pixels. During sliding the window, the noisy pixels are detected by calculating the maximum, minimum and the median values. Also in order to detect noise pixels position, the noised image was entered itself (target image) and pixel's Rank-Ordered Logarithmic Difference (ROLD) was estimated then noised pixels position in target image was detected. Dong *et al*. (2007) proposed a new local image statistic ROLD which is based on ROAD feature. It can identify more noisy pixels with less false hits and can be well applied to deal with random-valued impulse noise. Simulation results show that it outperforms a number of existing methods both visually and quantitatively. Based on this. Its definition is shown as follows. Firstly, the gray value of image was mapped, to a value of [0, 1] by linear transformation, that is (m) ∈ [0, 1]. This is the gray value of the pixel in image u at position m. The image has a window with its center on pixel (m) and its size is (2d+1)×(2d+1); pixel u (n) is one pixel in the window. The distance between the two pixels n and m is defined as Eq. 1:

$$D_{m,n} = 1 + \frac{\max\left\{\log_a\left|u(m)-u(n)\right|, -b\right\}}{\in N_m^0(d), \qquad k}, n \qquad (1)$$

Where, a, b>0. The best distinction is achieved when a = 2 and b = 5. Secondly, all D m was sorted in a window in a descending order. If noise density p>25%, then ROLD is the sum of the biggest 12 values sorted under a 5×5 window size. Otherwise, it is the sum of the biggest 4 values that are sorted under a 3×3 window size. For a variation between the noise pixel and its adjacent pixel in the window, the ROLD value will be a high integer. Based on this value, the ROLD of a normal pixel should be smaller for the consistency between itself and its adjacent pixel. Therefore, ROLD serves as an important definition of pixels and distinguishes between noise pixels and normal pixels (Hu *et al*., 2013). After detection the noisy pixel, the maximum, minimum, the median values and the standard deviation was calculated for the uncorrupted pixel while the corrupted pixel was reduced by niching genetic algorithms (Singh, 2018; Gangadhar *et al*., 2014).

Niching genetic algorithms: The suggested system utilizes niching genetic algorithm as a tool to choose the optimal features from the pool of initially extracted features. The idea of niching is applicable in an optimization of constrained problems. In such problems, maintaining diverse feasible solutions is desirable, so as to prevent accumulation of solutions only in one part of the feasible space, especially in problems containing disconnected patches of feasible region (Ye *et al*., 2011). Niching methods have been developed to minimize the effect of genetic drift resulting from the selection operator in the traditional GA in order to allow the parallel investigation of many solutions in the population. The advantages of this approach are the simplicity of implementation and the efficiency attained by parallel processing (Pereira and Sacco, 2008).

As stated by Perez *et al*. (2012), the comparisons between niching methods (crowding, fitness sharing and clearing) have shown that clearing methods are efficient in reducing the genetic drift and maintaining multiple stable solutions. However, in the canonical clearing approach, cleared individuals have no chance to participate in the mutation and crossover which limits the exploration capabilities of evolutionary process. To alleviate this problem the Context Based Clearing (CBC) procedure is utilized. CBC uses a fixed number of candidates in a clearing subpopulation rather than a fixed radius. Unlike the standard clearing procedure the CBC procedure makes use of local information to guide the clearing procedure. In addition, it avoids additional processing overhead by using a fixed radius (Fayek *et al*., 2010).

The CBC procedure is a clearing procedure that makes use of context information to prevent clearing candidates that may lead to significant optima. Context refers in this case to the fitness distribution within a certain area around pivot elements as explained below. Within the same area if candidates have similar fitness, it is safe to clear the complete area as then all candidates belong to the same optima. However, if candidate's fitness differs significantly (which is measured by the standard deviation as will be shown), it may cause loss of important data if the whole set of candidates is cleared. CBC is embedded within GA as shown in. It begins after evaluating the fitness of the individuals and before applying selection and crossover. The CBC procedure performs clearing according to the heterogeneity of the individuals within the subpopulation where heterogeneity is measured using the standard deviation of individual's fitness. Each subpopulation has a pivotal individual which is the individual with the highest fitness. The number of individuals in a subpopulation around a certain pivot is determined by the amount of similarity between individuals and the pivot (Pereira and Sacco, 2008; Perez *et al*., 2012) as shown in. The CBC procedure uses a number of parameters as follows.

Subpopulation Percentage (SP): Determines the proportion of individuals that fall within a subpopulation. These individuals are those nearest to the pivot of the subpopulation with respect to distance. The number of individuals within each subpopulation is calculated as:

$$M = SP\ population\_size/100 \quad (2)$$

Niche Radius (R): The threshold value for clearing candidates around the pivot in case of insufficient homogeneity of subpopulation.

N: Total number of individuals of the whole population, population_size.

N_β: Total Number of subpopulations.

Algorithm 1: CBC clearing niching procedure

Input: M, N, R, SP, N_β

1- Individuals of the whole population are sorted in descending order with respect to their fitness into a candidate queue
2- The highest fitness candidate in the candidate queue is selected as a pivot
3- Subpopulations are created
4- For each subpopulation
    4.1 Select pivot neighbors within the subpopulation around the pivot as determined by the SP parameter
4.2 Calculate the standard deviation of fitness values for the subpopulation to specify the beterogeneity among candidates of the subpopulation
4.3 If the standard deviation value is less than the given threshold then
    - The candidates in this subpopulation will becleared by setting their fitness to zero in the subpopulation as well as in the subpopulation as well as in the candidate queue
    Else
    - Only those candidates within a distance less then or equal to the nicehe radius with respect to the pivot will be cleared (again in the subpopulation as well as in the candidate queue)
5- The next candidate with fitness>0 in the candidate queue is taken as pivot. Then steps 1-4 are repeated
6- The winners of all subpopulations are stored in the global winners array
   This population enters crossover and mutation stage to generate the next new population

Here, in the threshold which ranges between minimum fitness value and maximum fitness value of the subpopulation candidates is empirically estimated. In general, the ability of the CBC procedure to verify the validity of clearing before applying it by checking the heterogeneity of the individuals within the subpopulation has prevented the clearing of local attractors at early stages and thus enabled it to reach solutions much earlier than standard clearing (Fayek *et al*., 2010; Kalra *et al*., 2017). In this case, an instance of a GA-image denoising problem can be described in a formal way as a four-tuple (R, Q, T, f) defined as (Ramberger, 2000; El-Sawy *et al*., 2014; Rosiyadi *et al*., 2012; Sivanandam and Deepa, 2007).

R is the solution space (initial population-consists of entirely random strings (chromosomes) which encode candidate solutions to an optimization problem evolves toward better solutions.

Q is the feasibility predicate (different operators selection, crossover and mutation). The crossover is the process of exchanging the parent's genes to produce one or two offspring that carry inherent genes from both parents to increase the diversity of the mutated individuals (Sivanandam and Deepa, 2007). Herein, a single point crossover is employed because of its simplicity. The purpose of mutation is to prevent falling into a locally optimal solution of the solved problem (Sivanandam and Deepa, 2007), a uniform mutation is employed for its simple implementation. The selection operator retains the best fitting chromosome of one generation and selects the fixed numbers of parent chromosomes. Tournament selection is probably the most popular selection method in genetic algorithm due to its efficiency and simple implementation is the set of feasible solutions (new generation populations). With these new generations, the fittest chromosome will represent the optimum solution for denoising is found (Ramberger, 2000; Rosiyadi *et al*., 2012; Sivanandam and Deepa, 2007; Sheikh *et al*., 2008).

f is the objective function (fitness function). The individual that has higher fitness will win to be added to the predicate operators mate. Herein, the fitness function is computed based on the equation related energy function that shows the difference between noisy image and recoverd image. Fitness is given by Fatiha:

$$\text{fitness}(X) = \mu\sum_{(u,v)\in N}|X_u\text{-}X_v|+\sum_{v\in V}\left(I(v)\text{-}X_v\right)^2 \quad (3)$$

Where:

X : The individual being evaluated

X_v : The v-th pixel of X

I(v) : The v-th pixel of the noisy image I

Two pixels (u; v) 2 N if and only if u and v are neighboring pixels in the 4-neighborhood. The constant μ balances the smoothness of X and its similarity with I. Algorithm 2 illustrates the pseudo code of the GA.

Algorithm 2: Genetic algorithm pseudo code

1. t = 0
2. Generate Initial Population [R(t)]
3. Evaluate Population [R(t)]
4. While not termination do
5. R'(t)= Variation [R(t)]
6. Evaluate population [R'(t)]
7. R (t+1) = Apply GA operators [R'(t)∪Q]
8. t = t+1

   End while

Performance evaluation: The qualitative assessment of the recovered image is done by forming a different (between the original and the recovered) image. For quantitative assessment of the restoration quality, the metrics used for performance evaluation: PSNR (Peak Signal to Noise Ratio) and MSE (Mean Square Error). It is the ratio in between the peak signal of the power and after it has been corrupted with noise.

$$\text{MSE} = \sum\left(\left(I_1\text{-}I_2\right)/m\times n\right)^2 \quad (4)$$

Where

I_1 : The noisy Image

I_2 : The original Image and

m×ni : Total size of image

$$\text{PSNR} = 20\log_{10}\frac{\text{MAX}^2}{\text{MSE}} \quad (5)$$

Where:

MSE : Mean Squared Error

MAX I : Maximum Intensity

PSNR : Peak Signal to Noise Ratio

RESULTS AND DISCUSSION

Experimental results: The image datasets included in this study are standard dataset from: (available at: https://homepages.cae.wisc.edu/~ece533/images/), the selected images are gray images to test the program and its performance. The suggested system has been implemented by MATLAB (2015). using the laptop computer with the following specifications: processor: Intel (R), Core (TM) i5-5200U CPU@220 GHZ@ 290 GHz. Installed memory (RAM): 4 GB. System type: 64-bit operating system, x64 based processor. Microsoft windows 10 Enterprise as running operating system.

Experiment 1: Influence of GA and NGA parameters: The suggested denoising Image that relies on niching Genetic algorithm has been tested with several benchmark image. The suggested system has been tested with different parameters to perceive the influence of these parameters on the system evaluation. After conducting several trials, the parameters of NGAs and GA are set as following: the size of population is 100. The probabilities

Table 1: Niching genetic algorithm and Genetic algorithms parameters used in the study

Parameter	Variables	Values
Population size	PS	100
No. of generation	NG	10
Mutation	M	0.3
Crossover	CO	0.8

Table 2: The effect of crossover ratio on the image denoising in terms of PSNR (Population size = 10, Generation No. = 100, Pm = 0.3)

Pc	PSNR
0.5	34.8887
0.6	34.9283
0.7	34.9561
0.8	**34.9562**
0.9	33.8667
1.0	33.2223

Table 3: The effect of mutation ratio on the image denoising in terms of PSNR (Population size = 100, Generation No = 10, Pc = 0.8)

Pm	PSNR
0.1	34.6232
0.2	34.7236
0.3	**34.9562**
0.4	34.8754

of crossover operation and mutation operation are 0.3 and 0.08, respectively. The termination criterion here includes setting the number of generation are 10. Which given best results as shown in Table 1.

The crossover (mutation) operator (item below) plays a fundamental role in a GA, through which it is possible for the population to diversify and maintain adaptation characteristics through generations. Considered the predominant operator, the crossover is responsible for the creation of new individuals by the blending of characteristics of the parent individuals by digitally simulating the natural process of gene blending (Eiben and Smith, 2003). So that, the effect of crossover ratio on proposed system was studied and the results was shown in Table 2 in which 0.8 gave the best results.

The mutation operation simply randomly modifies a characteristic of the chromosome in which it is being applied, this step is important to create new values of features previously non-existent or even that arise in low quantity (Eiben and Smith, 2003). As in the crossing step, the mutation occurs proportionally at a given probability rate. The best performance for the proposed system was in 0.3 mutation rate as illustrated in Table 3.

As shown in both tables, the results was closed to that mentioned by the studies of (Parvez and Dhar, 2013) on random mutation technique has shown that optimum probability of mutation lies between 0.0-0.3. At the same year revealed that the cross-over probability is positively associated with the mutation probability in the implementation of GA but correlation is not significant. While in the study of applying GA as a de-noising process and showed that it is a much more benefit as a de-noising techniques than the other techniques that used for comparison and the parameter setting for the process include population size 25, crossover propapility 0.4, mutation propability 0.01 and number of gene was 5 which applied to two grey scale images.

The second experiment was done to illustrates the effect of some variables of the genetic algorithm on the efficiency of the proposed system. In general, GA is a population based stochastic algorithm that exploits a population of potential solutions individuals, to effectively probe the search space. An issue when applying GAs is to determine a set of control parameters that balance the exploration and the exploitation capabilities of the given algorithm. Population size was vary in range (10, 25, 50, 100) while number of generation was changed in (5, 10, 20, 50) range as illustrated in Table 4 which revealed that the best performance for the system was with population size 100 and generation 10. There is always a tradeoff between the efficient exploration of the search space and its effective exploitation. In extreme cases, an inadequate choice of the parameter values can hinder the algorithm's ability to locate the optimum (Epitropakis *et al*., 2008). For example, if the mutation rate is too high, much of the space will be exploredbut there is a high probability of losing promising solutions; the algorithm has difficulty to converge to an optimum due to insufficient exploitation.

The metaheuristic algorithms require of setting the values of several algorithm components and parameters. These parameters values have great impact on performance and ef cacy of the algorithm (Nowotniak and Kucharski, 2012; Saremi *et al*., 2007; Fidanova, 2006). Therefore, it is important to investigate the algorithm parameters in uence on the performance of the developed metaheuristic algorithms. The aim is to nd the optimal parameters values for the considered optimization problem. The optimal values for the parameters depend mainly on the problem; the instance of the problem to deal with and the computational time that will be spend in solving the problem. Usually in the algorithm parameters tuning a compromise between solution quality and search time should be done. Population sizing has been one of the important topics to consider in evolutionary computation (Diaz-Gomez and Hougen, 2007. Various results about the appropriate population size can be found in the literature (Roeva, 2008). Researchers usually argue that a "small" population size could guide the algorithm to poor solutions (Koumousis and Katsaras, 2006; Pelikan *et al*., 2000) and that a "large" population size could make the algorithm expend more computation time in nding a solution (Koumousis and Katsaras, 2006; Lobo and Goldberg, 2004; Lobo and Lima, 2005). Due to signi cant in uence of population size to the solution quality and

Table 4: Effect of population size and number of generation on the system performance

Image	NG	PS	PSNR
Size 512	5	10	34.9495
		25	34.9497
		50	34.9508
		100	34.9512
	10	10	34.9511
		25	34.9528
Lena.bmp		50	34.9540
		100	**34.9562**
	20	10	34.9468
		25	34.9474
		50	34.9491
		100	34.9498
	50	10	34.9461
		25	34.9472
		50	34.9481
		100	34.9486
Size 256 256	5	10	34.9597
		25	34.9603
		50	34.9609
		100	34.9617
	10	10	34.9619
		25	34.9621
		50	34.9638
		100	**34.9646**
Cameraman.tif	20	10	34.9559
		25	34.9573
		50	34.9581
		100	34.9597
	50	10	34.9568
		25	34.9576
		50	34.95919
		100	34.9624
Size 640 480	5	10	34.9489
		25	34.9493
		50	34.9527
		100	34.9559
	10	10	34.9548
		25	34.9556
		50	34.9569
Mountain.bmp		100	**34.9577**
	20	10	34.9479
		25	34.9486
		50	34.9495
		100	34.9502
	50	10	34.9466
		25	34.9479
		50	34.9487
		100	34.9498

search time (Roeva, 2008) a more thorough research should be done for this GA parameter (Olympia *et al*., 2013).

Table 5: System performance evaluation regarding the niching Genetic algorithm for image after adding 10% noise density

Image data set	Noise type	Noise PSNR	PSNR GA	PSNR NGA
Lena.bmp	Gaussian	22.9211	25.1559	29.9516
Zelda.png		22.9208	25.1582	29.9573
Cameraman.tif		22.9195	25.2434	29.9406
Barbara.bmp		22.1676	25.1701	29.9308
Boat.png		22.9503	25.3516	29.9507
Mountain.bmp		22.9170	25.3451	29.9880
Peppers.jpg		22.9276	25.4221	29.9794
Baboon.jpg		22.9443	25.4232	29.9787
Lena.bmp		20.1983	27.1926	34.9562
Zelda.png	Salt and	20.0614	27.1972	34.9532
Goldhill.png	Papper	20.0643	27.1967	34.9552
Cameraman.tif		20.0783	27.1986	34.9646
Barbara.bmp		20.0831	27.1951	34.9623
Boat.png		20.0779	27.1943	34.9490
Mountain.bmp		20.0847	27.1989	34.9577
Peppers.jpg		20.0955	27.2014	34.9606
Baboon.jpg		20.0965	27.2020	34.9611
Lena.bmp	Speckle	21.9581	26.3501	30.9778
Zelda.png		21.9435	26.3441	30.9688
Goldhill.png		21.9502	26.4003	30.9777
Cameraman.tif		21.9568	26.4123	30.9855
Baboon.jpg		21.9569	26.4120	30.9856
Boat.png		21.9599	26.3996	30.9079
Mountain.bmp		21.9610	26.1022	30.9556
Peppers.jpg		21.9622	26.5214	30.9602
Baboon.jpg		21.9637	26.5228	30.9613

It has been recognized that if the initial population to the GA is good, then the algorithm has a better possibility of finding a good solution (Burke *et al*., 2004; Zitzler *et al*., 2000) and that if the initial supply of building blocks is not large enough or good enough, then it would be difficult for the algorithm to find a good solution. Sometimes, if the problem is quite difficult and some information regarding the possible solution is available, then it is good to seed the GA with that information, i.e., the initial population is seeded with some of those possible solutions or partial solutions of the problem. A measure of diversity plays a role here in the sense that when we have no information regarding a possible solution, then we could expect, that the more diverse the initial population is the greater the possibility to find a solution is and of course, the number of individuals in the population to get a good degree of diversity becomes important (Diaz-Gomez and Hougen, 2007).

Experiment 2: Performance accuracy with different noise density: The second set of experiments was performed to show how the noise density was affected on the quality of the proposed system in terms of PSNR depends on the Niching genetic algorithm. For each type of noise the testing images are corrupted separately by different levels and passed through, the proposed system then the PSNR value is computed for each image. In the following, the results for each type of noise are shown in Tables (5-9), it has been revealed that when applying 10%

Table 6: System performance evaluation regarding the niching genetic algorithm for image after adding 30% noise density

Image data set	Noise type	Noise PSNR	PSNR GA	PSNR NGA
Lena.bmp	Gaussian	19.9211	21.1559	25.9516
Zelda.png		19.9208	21.1582	25.9573
Goldhill.png		19.9100	21.1580	25.9580
Cameraman.tif		19.9195	21.2434	25.9406
Barbara.bmp		19.1676	21.1701	25.9308
Boat.png		19.7503	21.3561	25.9507
Mountain.bmp		19.7704	21.3451	25.9880
Peppers.jpg		19.8570	21.3634	25.9892
Baboon.jpg		19.8645	21.3656	25.9898
Lena.bmp	Salt and papper	18.1969	24.1926	32.9562
Zelda.png		18.0614	24.1972	32.9532
Goldhill.png		18.0643	24.1967	32.9552
Cameraman.tif		18.0783	24.1986	32.9646
Barbara.bmp		18.0831	24.1951	32.9623
Boat.png		18.0779	24.1943	32.9490
Mountain.bmp		18.0847	24.1989	32.9577
Peppers.jpg		18.1975	24.1992	32.9650
Baboon.jpg		18.1981	24.1997	32.9657
Lena.bmp	Speckle	20.9581	24.3501	27.5561
Zelda.png		20.9435	21.3441	27.6539
Goldhill.png		20.9502	24.4003	27.6558
Cameraman.tif		20.9568	24.4122	27.8781
Barbara.bmp		20.9569	24.4120	27.6626
Boat.png		20.9599	24.3996	27.7492
Mountain.bmp		20.9610	24.4022	27.5577
Peppers.jpg		20.9712	24.434	27.6011
Baboon.jpg		20.9721	24.442	27.7901
Lena.bmp	Poisson	21.9583	25.3506	29.5562
Zelda.png		21.9431	25.3448	29.6538
Goldhill.png		21.9508	25.4005	29.659
Cameraman.tif		21.9569	25.4124	29.5647
Barbara.bmp		21.9564	25.4120	29.6625
Boat.png		21.9593	25.3991	29.7494
Mountain.bmp		21.9610	25.4022	29.5577
Peppers.jpg		21.9620	25.4056	29.6530

noise density on the tested image that clearing niching genetic algorithms gave higher PSNR value in comparison with the GA and there is no effect mentioned when using different image type with same noise kind this finding was confirmed when increasing the noise density from 30-90% which mean that the suggested programme work effectively when applying image corrupted with high noise density as when using low density one. As mentioned in Table 5-8, respectively. It can be seen that for all noise levels, the outputs produced by CNGA based are denoised with considerable image detail preservation. This is clear from the fact that the previouse method, along with noise removal, retains the high density white spots in the denoised image, even when the input noise level is high (90%). Thus, it can be safely said that CNGA based can be used for removal all noise type with a minimal loss of significant details from the image (Fig. 3-7).

One possible explanation of these results is that the suggested system removing noise from a digital image (Image de-noising) is that clearing methods are efficient in reducing the genetic drift and maintaining multiple stable solutions. However, in the canonical clearing approach, cleared individuals have no chance to

Table 7: System performance evaluation regarding the niching Genetic algorithm for image after adding 50% noise density

Image data set	Noise type	Noise PSNR	PSNR GA	PSNR NGA
Lena.bmp	Gaussian	15.9211	17.1559	19.9516
Zelda.png		15.9208	17.1582	19.9573
Goldhill.png		15.9100	17.1580	19.9580
Cameraman.tif		15.9195	17.2434	19.9406
Barbara.bmp		15.1676	17.1701	19.9308
Boat.png		15.7503	17.3561	19.9507
Mountain.bmp		15.9847	17.1989	19.9577
Peppers.jpg		15.9850	17.2460	19.9586
Baboon.jpg		15.9845	17.2501	19.9593
Lena.bmp	Salt and papper	14.1587	18.1926	22.9561
Zelda.png		14.0614	18.1972	22.9537
Goldhill.png		14.0643	18.1967	22.9554
Cameraman.tif		14.0783	18.1986	22.9649
Barbara.bmp		14.0831	18.1951	22.9585
Boat.png		14.0779	18.1943	22.9491
Mountain.bmp		14.0847	18.1989	22.9579
Peppers.jpg		14.0924	18.1991	22.9601
Baboon.jpg		14.0931	18.1989	22.9621
Lena.bmp	Speckle	17.8990	20.9926	23.9561
Zelda.png		17.8959	20.9972	23.9537
Goldhill.png		17.8977	20.9967	23.9554
Cameraman.tif		17.8967	20.9986	23.9649
Barbara.bmp		17.8986	20.9951	23.9625
Boat.png		17.8944	20.9943	23.9491
Mountain.bmp		17.8997	20.9989	23.9579
Peppers.jpg		17.8993	20.9991	23.9602
Baboon.jpg		17.8999	20.9893	23.9606
Lena.bmp	Poisson	18.9583	21.7506	24.8562
Zelda.png		18.9431	21.7448	24.8538
Goldhill.png		18.9508	21.7005	24.8559
Cameraman.tif		18.9569	21.7124	24.8647
Barbara.bmp		18.9564	21.7120	24.8625
Boat.png		18.9593	21.7991	24.8694
Mountain.bmp		18.9610	21.7022	24.8577
Peppers.jpg		18.9622	21.7200	24.8601
Baboon.jpg		18.9638	21.7236	24.8670

participate in the mutation and crossover which limits the exploration capabilities of evolutionary process. In multi-modal optimization domain, two criteria are generally used to measure the success of the search algorithms. First, whether an optimization algorithm can find all desired global/local optima within reasonable amount of time and the second, if is capable of stably maintaining multiple candidate solutions. Clearing method for niching is successful in achieving the latter, however, it falls short in former criterion. We are interested not only in stably identifying one or more global optima but we are interested to locate set of all acceptable solutions in timely manner.

Experiment 3: Comparison with previous studies: The third experiment is comparison with existing methods, the performance of the proposed system was compared with that done by the previous researcher, some methods according to published papers (Toledo *et al.*, 2013; Rabila and Bharatha, 2016) are re-implemented. Toledo *et al.* (2013) described a novel image denoising method based on Genetic algorithms. A new algorithms was proposed by

Table 8: System performance evaluation regarding the niching Genetic algorithm for image after adding 70% noise density

Image data set	Noise type	Noise PSNR	PSNR GA	PSNR NGA
Lena.bmp	Gaussian	11.9211	13.1559	15.9516
Zelda,pug		11.9208	13.1582	15.9573
Goldhill.pug		11.9100	13.1580	15.9580
Cameraman.tif		11.9195	13.2434	15.9406
Barbara.bmp		11.1676	13.1701	15.9308
Boat.pug		11.7503	13.3561	15.9507
Mountain.bmp		11.9847	13.1989	15.9577
Peppers.jpg		11.9850	13.1993	15.9569
Baboon.jpg		11.8990	13.1990	15.9578
Lena.bmp	Salt and	10.9988	13.9988	16.9561
Zelda.png	Papper	10.3456	13.3456	16.9537
Goldhill.png		10.8998	13.8998	16.9554
Cameraman.tif		10.7898	13.7898	16.9649
Barbara.bmp		10.9789	13.9789	16.9625
Boat.pug		10.9687	13.9687	16.9491
Mountain.bmp		10.9678	13.9678	16.9579
Peppers.jpg		10.9680	13.9710	16.9601
Baboon.jpg		10.9701	13.9778	16.9620
Lena.bmp	Speckle	14.1981	16.9926	18.9561
Zelda.png		14.0614	16.9972	18.9537
Goldhill.png		14.0643	16.9967	18.9554
Cameraman.tif		14.0783	16.9986	18.9649
Barbara.bmp		14.0831	16.9951	18.9625
Boat.pug		14.0779	16.9943	18.9491
Mountain.bmp		14.0847	16.9989	18.9579
Lena.bmp	Poission	15.9583	17.7506	19.8562
Zelda.png		15.9431	17.7448	19.8538
Goldhill.png		15.9508	17.7005	19.8559
Cameraman.tif		15.9569	17.7124	19.8647
Barbara.bmp		15.9564	17.7120	19.8625
Boat.pug		15.9593	17.7991	19.8494
Mountain.bmp		15.9610	17.7022	19.8577
Peppers.jpg		15.9646	17.7044	19.8634
Baboon.jpg		15.9652	17.7052	19.8701

Table 9: System Performance Evaluation Regarding the Niching Genetic Algorithm for Image after Adding 90% Noise Density

Image Data Set	Noise Type	NOISE PSNR	PSNR GA	PSNR NGA
Lena.bmp	Gaussian	9.9211	10.9559	11.6516
Zelda,pug		9.9208	10.9582	11.6573
Goldhill.pug		9.9100	10.9580	11.6580
Cameraman.tif		9.9195	10.9434	11.6406
Barbara.bmp		9.1676	10.9701	11.6308
Boat.pug		9.7503	10.9561	11.6507
Mountain.bmp		9.9847	10.9989	11.6577
Peppers.jpg		9.8094	10.9956	11.7010
Baboon.jpg		9.9228	10.9989	11.7031
Lena.bmp	Salt and	8.2981	11.9879	12.1177
Zelda.png	Papper	8.2614	11.9676	12.1262
Goldhill.png		8.2643	11.9775	12.1262
Cameraman.tif		8.2783	11.9886	12.1442
Barbara.bmp		8.2831	11.9665	12.1332
Boat.pug		8.2779	11.9884	12.1132
Mountain.bmp		8.2847	11.9557	12.1122
Peppers.jpg		8.2933	11.9632	12.1248
Baboon.jpg		8.2965	11.9759	12.1678
Lena.bmp	Speckle	12.8990	13.1123	14.9561
Zelda.png		12.8959	13.1332	14.9537
Goldhill.png		12.8977	13.1422	14.9554
Cameraman.tif		12.8967	13.1133	14.9649
Barbara.bmp		12.8986	13.1323	14.9625
Boat.pug		12.8944	13.1673	14.9491
Mountain.bmp		12.8997	13.1546	14.9579
Peppers.jpg		12.8988	13.1633	14.9635
Baboon.jpg		12.9112	13.2645	14.9647
Lena.bmp	Poission	13.9583	14.1527	15.8562
Zelda.png		13.9431	14.7448	15.8538
Goldhill.png		13.9508	14.7005	15.8559
Cameraman.tif		13.9569	14.7124	15.8647
Barbara.bmp		13.9564	14.7120	15.8625
Boat.pug		13.9593	14.7991	15.8494
Mountain.bmp		13.9610	14.7022	15.8577
Peppers.jpg		13.9730	14.7110	15.8643
Baboon.jpg		13.9723	14.7503	15.8900

Fig. 3 (a-c): Denoising of lena image corrupted with 10% noise density (a) Original image (b) Noisy images and (c) Corresponding denoised image by the proposed system

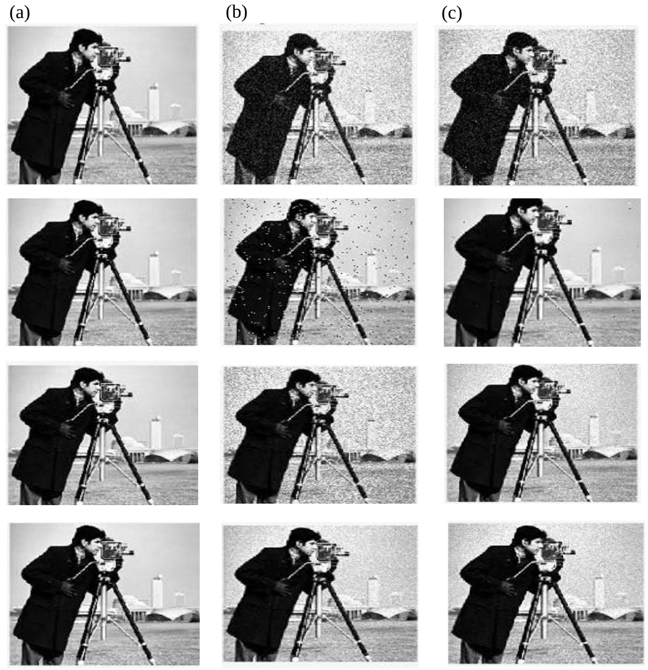

Fig. 4 (a-c): Denoising of cameraman image corrupted with 30% noise density (a) Original image (b) Noisy images and (c) Corresponding denoised image by the proposed system

Fig. 5 (a-c): Denoising of Barbara image corrupted with 50% noise density (a) Original image (b) Noisy images and (c) Corresponding denoised image by the proposed system

Rabila and Bharatha (2016) to improve the noise estimation of digital images with the support of IVT2FS filters and genetic algorithm. While in the study of a method of PCNN by combining the Genetic Algorithm (GA) and ant colony algorithm is proposed which named as GACA and the optimized procedure is named as GACAPCNN. In the study of display the results of different approaches of

Fig. 6 (a-c): Denoising of Goldhill image corrupted with 70% noise density (a) Original image (b) Noisy images and (c) Corresponding denoised image by the proposed system

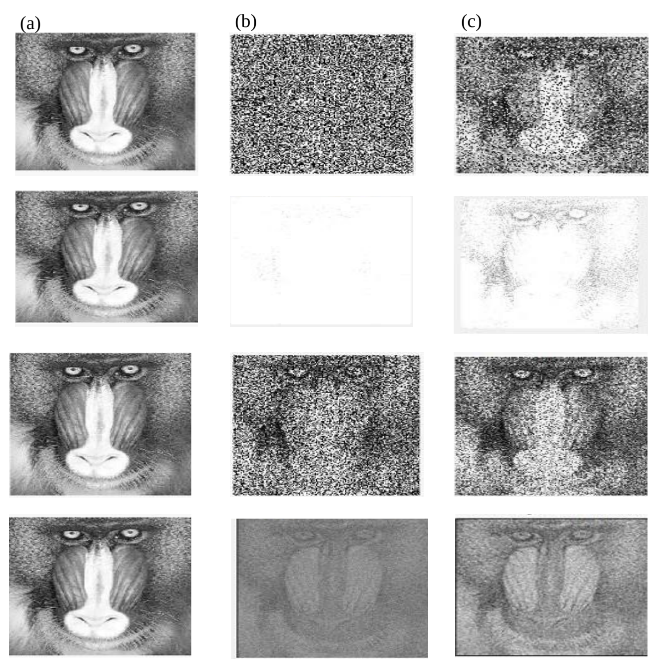

Fig. 7 (a-c): Denoising of paboon image corrupted with 90% noise density (a) Original image (b) Noisy images and (c) Corresponding denoised image by the proposed system

wavelet based image denoising methods using several thresholding techniques such as Bayes shrink, Sure Shrink and Visu Shrink and filters like mean filters.

From Table 9, it can be seen that the proposed method is better than the previous methods in PSNR, through the experiments, the performance of the proposed

Table 10: Comparison results of the existing methods

Method	PSNR
GA	30.94
IVT2FSs-GA	29.95656
GACAPCNN	33.94
VisuShrink	21.22
Mean filters	27.43
Proposed model	34.9562

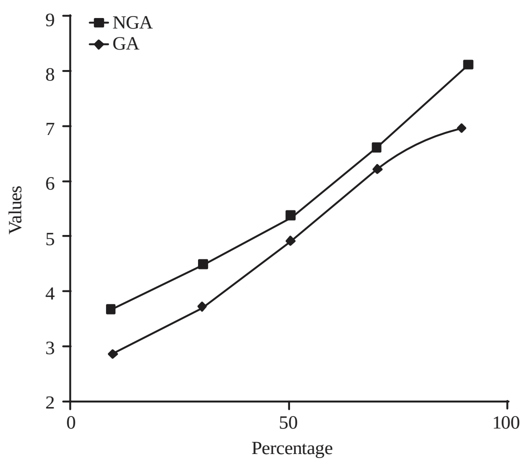

Fig. 8: Time complexity of the suggested system

method is verified and the quality of the image shows a great improvement compared to other conventional denoising methods, i.e., AD filter, Wiener filter, mean filter and median filter (Table 10).

Experiment 5; System complexity: The last set of experiment was conducted to evaluate the complexity of the suggested system. Time complexity analysis is a part of computational complexity theory that is used to describe an algorithm's use of computational resources; in most cases, the worst case running time expressed as a function of its input using big-O notation (Sanchez *et al*., 2016). As the proposed system was built using Matlab which in turn depends on calling many built-in functions, therefore, it is difficult to extract the big-O, herein; computation time is an important indicator when weighing an algorithm for it reflects whether the algorithm can be practically applied or not (Dong *et al*., 2007). The proposed algorithm includes two: noise detection and noise filtering. Experiments were done on images under 10-90% noise densities as shown in more processing time is needed for the suggested system as compared to the traditional Genetic algorithms (Fig. 8).

It has been noticed that the suggested system takes about 3.7 sec for the proposed system and takes about 2.9 sec for the traditional genetic algorithms, thus, the time of niching genetic algorithm is roughly equivalent to one more than the time of traditional genetic. In general, this relatively large time in the selection process represents clearing step of the proposed system. Consequently, the proposed system is applicable in real-time applications. Also, it shows that time of noise removal was grows when noise density grows.

CONCLUSION

In this study, a novel research has been established an efficient algorithm to remove noise has been established inspired by the challenges that faced the other image denoising techniques. The usage of the clearing NGA method has proven to improve the accuracy of the image denoising because it gives better results. The noise detection step was added, since, not every pixel is filtered, undue distortion can be avoided as far as possible. In general, utilizing niching genetic algorithm offers certain benefits as a tool to determine optimal feature selection for image denoising. Two of those benefits are highlighted.

A niching method is able to maintain multiple diverse solutions and preserve them for the entire duration of the GA run. Under the effect of niching, the population of solutions is dynamically stable under the selection pressure. In general, maintaining diverse feasible solutions is desirable so as to prevent accumulation of solutions only in one part of the feasible space, thus, diminishing the time complexity of a person's identification process. Utilizing context information for building a niching procedure helps the suggested model to build discriminative feature vectors depending on a small dataset. Thus, giving efficiency to the proposed model for working on small data set instead of exploiting a large sample of data to build a feature vector which in turn requires considerable time.

To set a plan for future works the system can be upgraded to work with image color with a camera instead of the grayscale image. Furthermore, adaptive NGA fitness sharing can be tested, the neural algorithm can be replaced with another appropriate one to fine tuning parameters and then the result should be evaluated to deduce the better optimization approach. The NGA can be replaced with another appropriate optimization method to find optimal denoising method. In general, the application of the offered system faces some constraints that include using a grayscale image (not a color image camera to efficiently apply the NGA algorithm, working with color image requires applying the same steps to each color channel, finally, extra memory space is needed to store some information that are used in the denoising process.

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