An Enhancement Visual Quality of Digital Medical Image Based on Hybrid Genetic Algorithm and Salp-Swarm Optimization.

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Abstract:

This paper proposed a method to denoise medical images using a Hybrid Adaptive Algorithm based on the Genetic Algorithm (GA) and Salp-Swarm Algorithm (SSA). Medical images can be often affected by different kinds of noise that decrease the precision of any automatic system for analysis. Therefore, the noise reduction methods are frequently utilized for increasing the Peak signal-to-noise ratio PSNR and the structural similarity index measure SSIM to optimize the originality. Gaussian noise speckle noise, Poisson noise, and salt & pepper noise corrupted the used medical data, separately with the different noise levels to medical images were added noise variance from 0.1 to 0.9. In the analytical study, we apply different kinds of noise like Gaussian noise (GN), speckle noise, Poisson noise, and Salt-and-pepper noise (SPN) to medical images for making these images noisy. The hybrid GA-SSA model was applied on medical noisy images and the performances have been determined by the statistical analyses such as PSNR values are gotten (54.84967, 51.98685, 43.57169, 45.4709), MSE equal (0.99075, 0.997525, 1.14925, 2.218438) Gaussian noise (GN), salt-and-pepper noise (SPN), Poisson noise, and speckle noise (SN) on order.

Keyword: Salp-Swarm Algorithm, Genetic Algorithm, Hybrid Salp-Swarm-Genetic Algorithm, Medical image, Noise reduction.

تحسين الجودة البصرية الامثل للصورة الطبية الرقمية على أساس خوارزمية جينية هجينة وخوارزمية Salp-Swarm.

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الخلاصة:

اقترح هذا البحث طريقة لخفض الضوضاء في الصور الطبية باستخدام خوارزمية تكيفية هجينة (HAA) تستند إلى الخوارزمية الوراثية(GA) وخوارزمية(SSA).الصور الطبية يمكن أن تتأثر في كثير من الأحيان بأنواع مختلفة من الضوضاء التي تقلل من دقة أي نظام تلقائي للتحليل. ولذلك كثيرا ما تستخدم طرق خفض الضوضاء لزيادة معدل ذروة الإشارة إلى الضوضاء PSNR ومقياس مؤشر التشابه الهيكلي SSIM للوصول إلى المستوى الأمثل لأصالة الصورة.

ضوضاء Gaussian،ضوضاء Speckle،ضوضاء Poisson وضوضاء Salt&Paper أفسد البيانات الطبية المستخدمة ،بشكل منفصل مع المستويات المختلفة من الضوضاء للصور الطبية أضيفت ضوضاء من ٠,١ إلى ٠,٩.

في الدراسة التحليلية، نطبق أنواعاً مختلفة من الضوضاء مثل ضوضاء Gaussian، ضوضاء Speckle ،ضوضاء Poisson وضوضاء Salt & Paper على الصور الطبية لإثارة الضوضاء فيها. تم تطبيق النموذج الهجين GA-SSA على الصور الطبية وتم تحديد الأداء من خلال التحليلات الإحصائية مثل قيم PSNR التي تم الحصول عليها (54.84967، ٥١,٩٨٦٨٥،٤٣,٥٧١٦٩،٤٥,٤٧٠٩)، MSE قيم مساوية لـ (0.99075 ، ٠,٩٩٧٥٢٥ ، ١,١٤٩٢٥ ، ٢,٢١٨٤٣٨) ضوضاء Gaussian، ضوضاء Speckle ،ضوضاء Poisson وضوضاء Salt & Paper .

الكلمات المفتاحية: خوارزمية Salp–Swarm، خوارزمية وراثية،خوارزمية هجين–Salp–Swarmوراثية،صور طبية،خفض الضوضاء.

1. Introduction:

Enhanced medical images are useful for physicians to provide accurate documentation and the images are frequently associated in the clinic–related fields, therefore, it is recommended to employ image enhancement in medical images [1]. Through using numerous techniques, medical images can be produced i.e., MRI, ultrasound, CT, and X-Ray. Different ways of thinking based on knowledge have different abilities to analyze the same image, especially the medical image with noise. [2]. To solve this problem, it is very important to use computer technology to enhance medical images. To denoise images and obtain better images, image enhancement can be utilized due to its importance and tract ability [3]. The objectives of this study focus on the set filters chosen by hybrid GA-SSA for increasing visual quality and saving medical image edge and building adaptive model related to the different kinds of medical images. A comparison is made to the advanced algorithms/methods performance with the existing ones regarding peak signal-to-noise ratio (PSNR), Mean Square Error (MSE), structural similarity index measure (SSIM), and SNR (Signal to Noise Ratio). The remainder of the paper is structured as follows: The second portion featured a review of relevant work, as well as a brief discussion of noise, the Salp-Swarm algorithm, and the genetic algorithm, the work methodology, discussion of the results, and conclusion were then provided in the following parts.

2. Related work

We present some researchers working denoising image field, Saraiva, A., et al. [4], 2019 introduced the development of a combined technique by using genetic algorithm technique, through this method, optimal filtration can be obtained and artifacts can be reduced. The algorithm structure functions in two basic methods, *the first method*: is to filter with BM4D, 3d medium filter, and ellipsoid filter. *The second step* is conducted by applying mutation operators in images that are recovered previously using intensity-change techniques, Gaussian filter, and medium filter, and provide an efficiency of the model adopted as a filter is shown with good application results. Yousefi Moteghaed, N., et. al [5] 2020, applied different kinds of noise like Gaussian noise and Salt-and-pepper noise to medical images for making these images noisy. Moreover, there are nine filters used in the study, to denoise medical images as Digital Imaging, the filters used are as follows: (1) Sigma filter (2) Log filter (3) Wiener filter (4) unsharp filter (5) average filter (6) Gaussian filter (7) Min filter (8) Max filter (9) Median filter. The denoising algorithm proposed has shown a significant increase in images' visual quality the statistical evaluation, the values of PSNR values are gotten between 59 to 63 and 63 to 65 for CT and MRI images. Asokan, Anju, et al. [6] 2020 present optimized contrast stretching using non-linear transformation to enhance images, selecting control parameters appropriately for sample images will affect the non-linear transformation because of the tediousness of the manual adjustment of individual images. Obviously, the contrast enhancement that depends on the Salp-Swarm algorithm is outperforming the other types of algorithm methods regarding metrics like Absolute Mean Brightness Error (AMBE), Mean Square Error, PSNR, and Entropy and CPU time (Central Processing Unit). Ting, Fung Fung [7] presented a method to estimate noise, called Adaptive Tuning Noise Estimation (ATNE) which applies Convolution Laplacian for estimating noise. The proposed method is based on subtraction of Gabor Wavelet-based edge detection of images and includes the element-based relation on the input image parameters.

2.1 Sources of Noise and Mathematical Representation of Noise

In the processes of acquisition, transmission, storage, and retrieval, noise image corrupts image signal. In many applications related to engineering, acquisition noise is usually low-contrast, and the basic cause is attributed to sensors' high quality [8]. The main clarification of that method is the system of image acquisition is composed of a transmitting tube. Salt-and-pepper noise and Additive white Gaussian noise, and mathematical formula are described below GN correspondingly distributed over signal, i.e. each pixel in the noisy image is representing actual values of pixel sum and random noise value with a given distribution is given by equation.1 [9].

$$F_{awgn} = f(x, y) + \eta_G(x, y) \qquad \text{............. (1)}$$

Where $\eta_G{}^a$ represent random variable having Gaussian probability distribution and a bell-shaped function of a probability distribution that is given in equation .2

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2} \qquad \text{............ (2)}$$

Where g refers to the grayscale, m refers to average or mean of the function and σ refers to noise standard deviation

2.2 Salp-Swarm Algorithm

The SSA is a recent nature-inspired optimizer proposed by Mirjalili et al. [10] in 2017. The SSA aims to generate a population-based optimizer via simulating the behavior of salp swarm in nature SSA algorithm reveals satisfactory diversification and intensification propensities that make[11]. In general, it regards as a flexible algorithm, capable, easy to be understood, simple and used in parallel and serial modes. Moreover, SSA has a single minimizing variable to make the best-fit balance between exploitation and exploration [12].

The position vectors of salps are gradually reworked, taking into account other salps in a dynamic crowd to prevent immature convergence with local optima (LO). The dynamic movements of salps boost the SSA's search ability to avoid LO and untimely convergence disadvantages. It also maintains elite salp100, which has until now been found, to guide other swarm members to better areas[13]. Thus it produces and develops random individuals (i.e., salps) within the boundary box of the problem iteratively. All salps should then update their vectors of location (chain leader and followers). The leader salp attacks in the direction of a food source (F), whereas all follower can directly or indirectly move the rest of the salps. An illustration of salp chain is shown in figure 1[14].

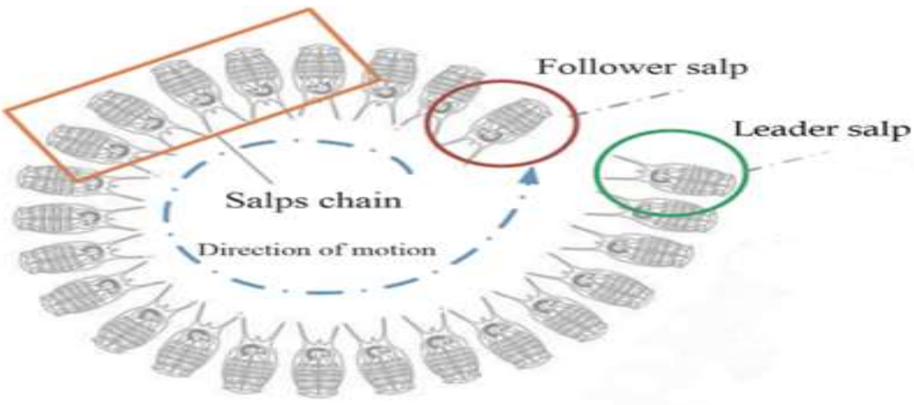

Figure 1 : Illustration the salp's chain movement [14]

The mathematical model of the salp chain consists of a population that classified into two groups: leader and followers. The front of the chain is a salp leader while the other salps considered as followers. As explained above, the salp leader guides swarm and the followers follow each other[15].

$$x_j^i = f(x) = \begin{cases} f_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) c_3 \geq 0 \\ f_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) c_3 < 0 \end{cases} \quad \ldots\ldots\ldots\ldots\ldots (3)$$

Where x_j^1 refers to salp leader position (the first) of dimension *j*th, the food source position of *j*th dimension is F_j, the upper bound of *j*th dimension is ub_j, the lower bound of *j*th dimension is lb_j, the leader updates its position with respect to the food source by c_1, c_2, and c_3 coefficient numbers counted randomly.$c_1$refers to the active parameter in the algorithm, because of the parameter balances between exploitation and exploration defined as:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Moreover, c_2 and $c_3$parameters as numbers uniformly generated between [0,1] interval. Practically, they trend if the next position in *j*th dimension should be towards positive infinity or negative infinity as well as the step size.

The position of the followers is updated by the following equations (Newton's law of motion):

$$x_j^i = \frac{1}{2}at^2 + v_0 t \quad \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where i ≥ 2,x_j^irefers to the position follower salp of *j*th dimension, t refers to time, the initial speed is v_0, and $a = \frac{v_{final}}{v_0}$ where $v = \frac{x - x_0}{t}$ because the time in optimization is iteration, the period between changing iteration is equalto1 with respect v_0= 0. From above, the equation can be expressed as below:

$$x_j^i = \frac{1}{2}\left(x_j^i - x_j^{i-1}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where i ≥ 2,x_j^i and x_j^i shows the position of follower salp in *i*th dimension [13,14,15,16].

2.3 Genetic algorithm

Genetic algorithm is a computation –related algorithm technique, which can search each part of the solution space using different type of solution or subset characteristics for finding the optimum answer for every iteration. In this algorithm, in the process of searching is simply needed for determining the value of the objective function value in various points and extra information is not required such as differentiating any function. The most important operator in genetic algorithm is crossover operator, which can produce a new population through a combination of chromosome relying upon their selection. The selected parents for crossover, transmit their genes jointly for creating a new offspring. Crossover has the ability of eliminating genetic variation in the population. Moreover, another operator in genetic algorithm is mutation operator that can produce multiple optimal solutions. In mutation, it is possible to remove a single from the subset or produce a new one that is added to the population [17,18]

3. Proposed Algorithm

This work applies the Genetic-Salp-Swarm Algorithm (GSSA) as a denoising technique of medical images for many types of noise and this technique is compared with median filter, Gaussian filter, bilateral filter, wiener filter. In work proposes (GSSA) to denoise the medical image achieved by the first step generation, initializing population by applying deffreint filters having different characteristics. The genetic algorithm is applied to modify the existing population, then the global best and local best of participation are selected, then the population is updated based on GSSA and updating the global and local best enhancement image, see algorithm 1 and figure 1.

Algorithm (1) Algorithm of the Genetic-Salp-Swarm for denoising medical image explained in the following steps:
Input: Noisy image **Output:** Denoised image

- Evaluate the fitness of every salp based on PSNR.
- Initial population by apply a number of filters with deferent parameter on the input image
- Initial number t=0
for i=1: to pop do
generation the initial population x(t) by apply a number of filters with deferent parameter on the input image
end for
Evaluate the fitness function of all individual based on PSNR.
Assign the overall best solution in the population
Determine the parmeter ub, lb where the ub is 255 and lb is 0
repeat
update c according eq 4
for i=1 to pop
if (i==1)
update the postion of the leader salp x(t) as shown eqation 3
else
update the postion of the follower x(t) as shown eqation 6
endif
update the salp based on the ub and lb
end for
set t=t+1
computing each image's fitness
From the current population, the two-maximum fitness of image is selected
Crossover the two image-based on single-point crossover
Replacing image's two minimum fitness by the two new image
computing the best local of the new population
updating the best global
if the fitness of best global image< fitness of the best local image
best global image = best local image
End for
Returning the best global image

4. Simulink Result and Discussion

In this work, number filters are applied and us (MATLAB R2021a) is implemented and different kinds of noise are tested: Gaussian noise speckle noise , poisson noise, and salt and pepper noise. The denoising from the image using Genetic-Salp-Swarm algorithm, Gaussian filter, bilateral filter, median filter, and wiener filter. The work test on several medical digital images of different kinds like CT, ultrasound, x-ray, MRI, in various formats ('.jpg', '. png', '.bmp'). A comparison is made to the results of methods proposed using the Genetic-Salp-Swarm algorithm value of image denoising with median filter, bilateral filter, Gaussian filter, and Wiener filter with various kinds of noise, see Fig 2, Fig 3.

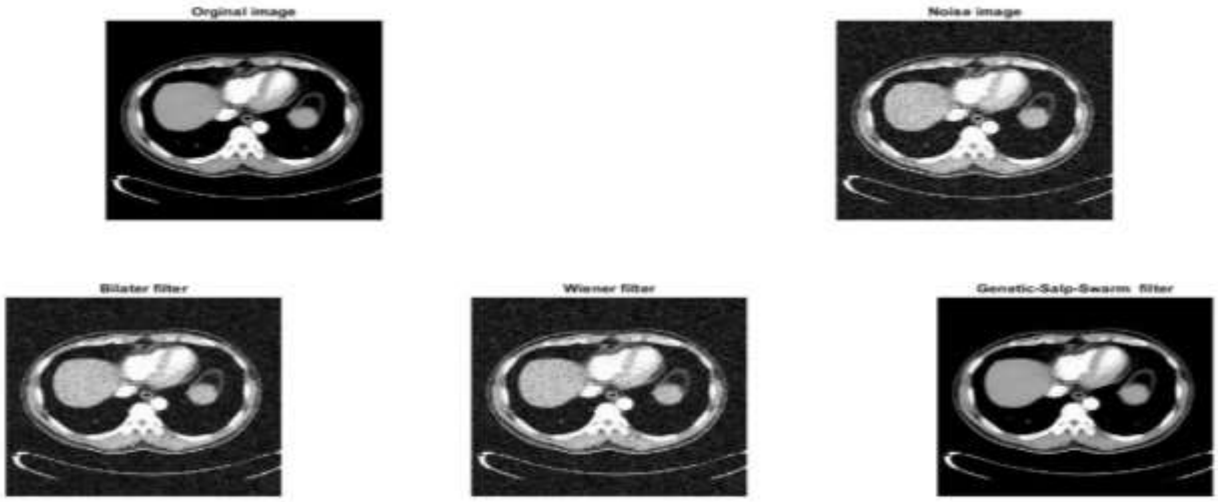

Figure 2: CT Image Denoise Gaussian Noise

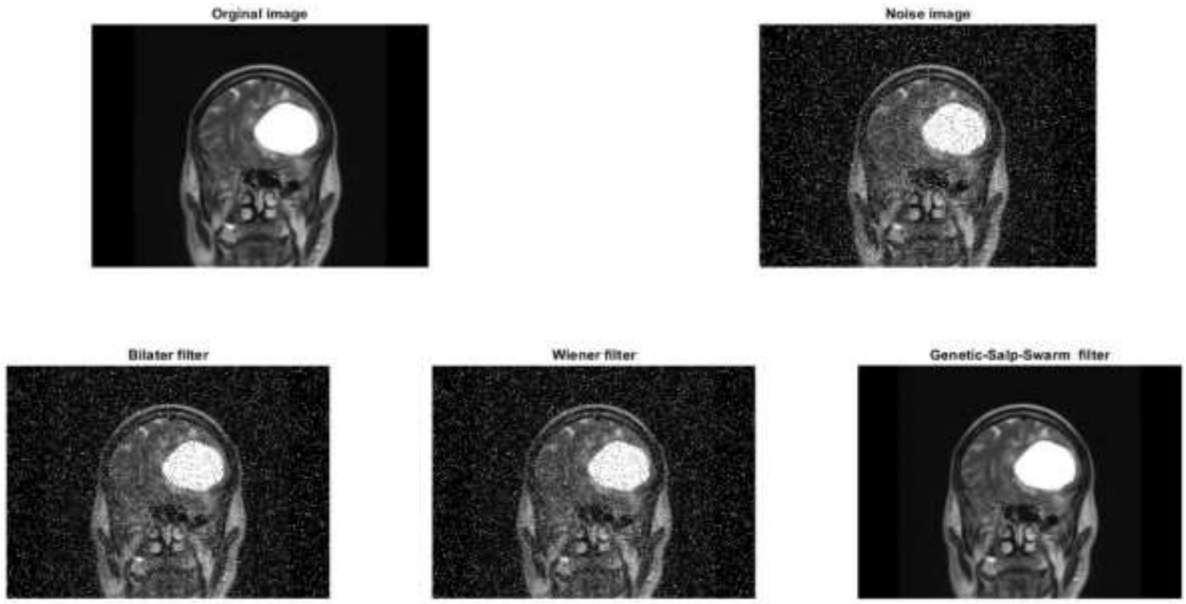

Figure 3: The MRI Image Denoise Salt Pepper Noise

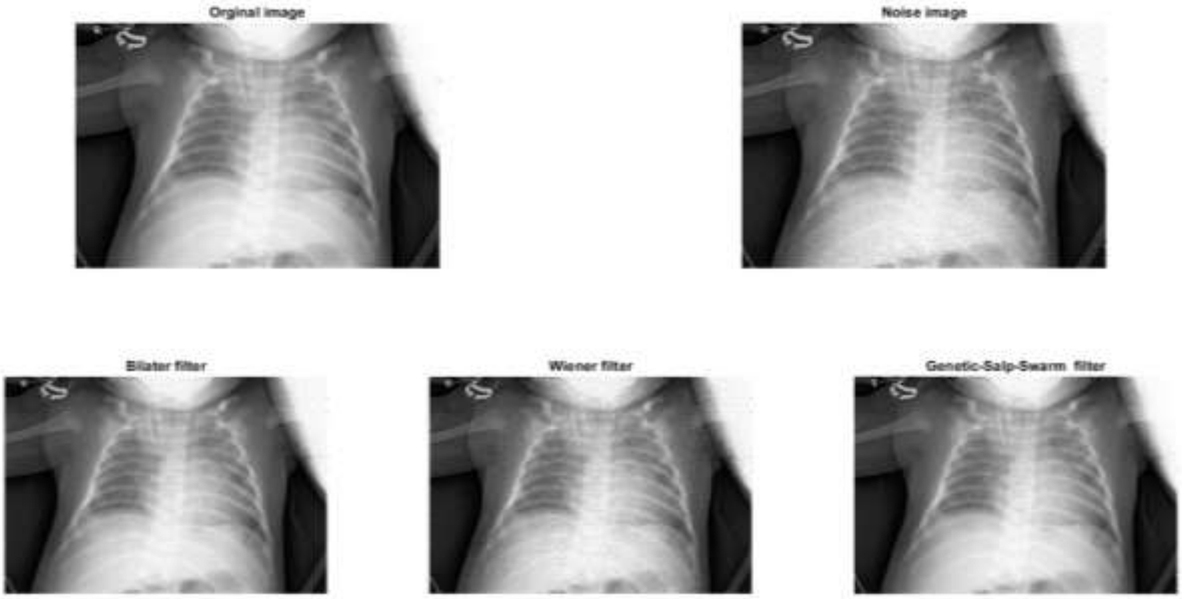

Figure 4: Xray Image Denoise Poisson Noise

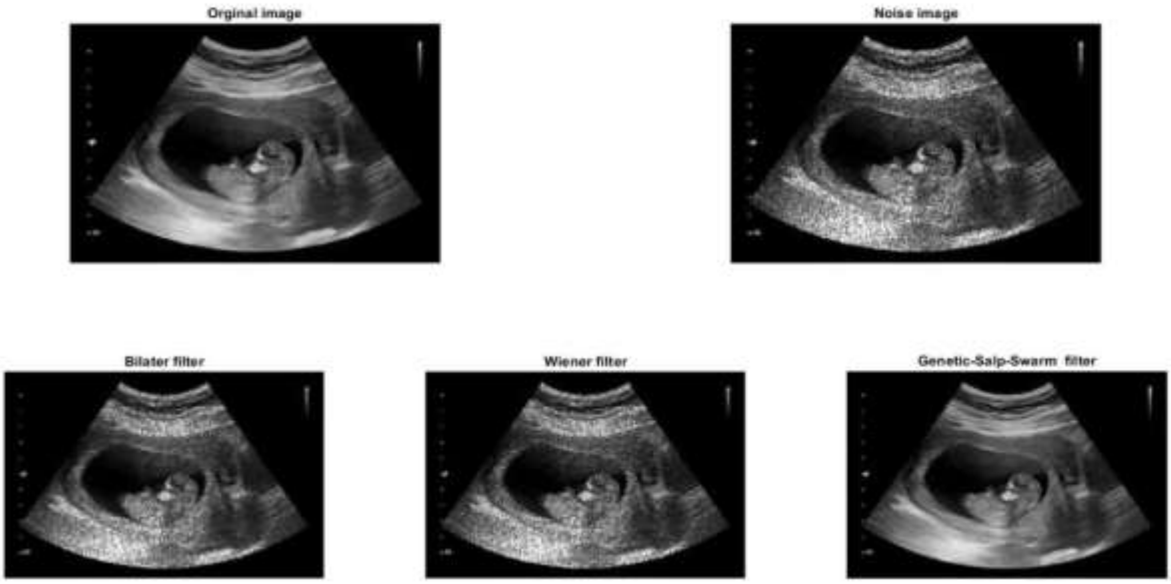

Figure 5: The Ultrasound Image Denoise Speckle Noise

Form figure (2,3,4,5) experiment follows these steps: first, a medical image is selected from the dataset, and noise is added to the image. The noise variance level ranging from 0.1 to 0.9 is added to the different type of medical image. Which Gussain noise, Speckle noise, Poisson noise was used to corrupt it, with noise variance from 0.1 to 0.9 is denoised by using the Genetic-Salp-Swarm algorithm and different traditional filters, and evaluating the proposed method performance, PSNR, MSE and SSIM values are determined as a quality metric.

Table 1: The performance of the proposal filter with other filters

Denoising results for Gaussian Noise						
	Level noise 0.1			Level noise 0.4		
Filter	PSNR	MSE	SSIM	PSNR	MSE	SSIM
Medean filter	21.07666	11.87175	0.444045	16.02	12.192	0.363251
Gaussian filter	20.42799	11.79975	0.375764	15.96	14.511	0.318305
Bilateral filter	20.18071	10.1565	0.356143	15.87	15.66075	0.303603
Wiener	21.13287	8.8155	0.472131	16.11	9.42975	0.381586
Genetic-Salp-Swarm	54.84967	0.99075	0.989465	51.3812	1.0572	0.989267
Denoising results for removing Salt and Pepper Nosie						
	Level noise 0.1			Level noise 0.4		
Filter	PSNR	MSE	SSIM	PSNR	MSE	SSIM
Medean filter	28.1655	14.93775	0.444817	26.059	15.6475	0.363865
Gaussian filter	31.4248	19.86	0.37521	22.704	22.866	0.31878
Bilateral filter	28.9828	16.7025	0.3564	24.838	22.0215	0.30393
Wiener	32.131	15.0525	0.47223	23.914	17.49675	0.38115
Genetic-Salp-Swarm	51.98685	0.997525	0.989762	46.3275	1.17725	0.989406
	Denoising results for Poisson Noise removal			Denoising results for Speckle Noise removal.		
Filter	PSNR	MSE	SSIM	PSNR	MSE	SSIM
Median filter	18.00843	209.2208	0.456618	21.40226	208.8435	0.490703
Gaussian filter	18.62289	219.4125	0.383021	17.73849	223.7513	0.322344
Bilateral filter	19.53633	79.245	0.363152	20.3038	209.2148	0.363152
Wiener filter	20.25342	91.995	0.483496	21.5116	209.0595	0.253747
Genetic-Salp-Swarm	43.57169	1.54925	0.989475	45.4709	1.218438	0.989475

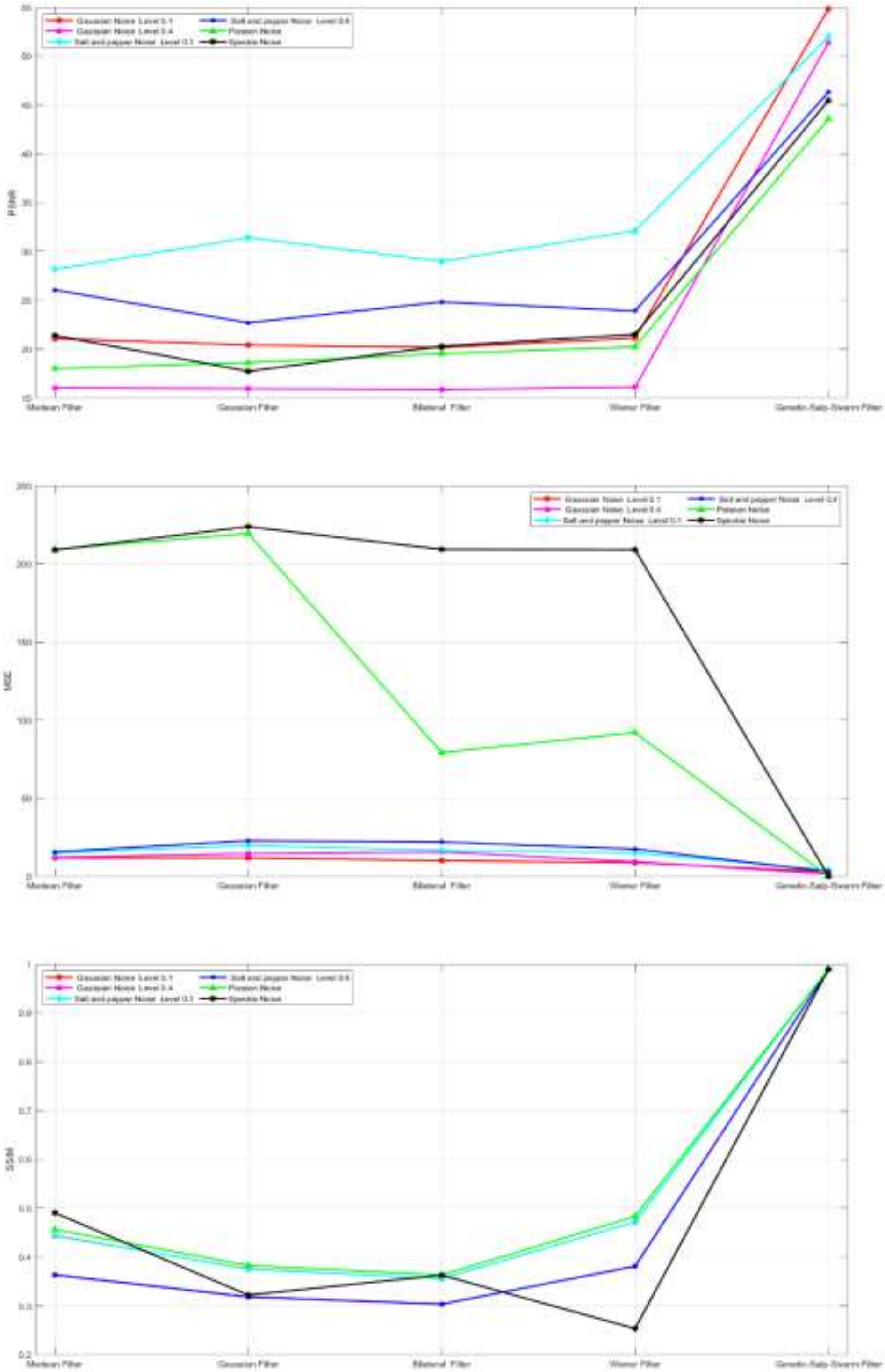

Figure 6: Denoising results for Gaussian Noise removal.

Through the above table(1) and figure(6), that the proposed genetic-Salp-Swarm filter achieved higher results when compared with the traditional filter with various types of Noise, where it achieved the highest results in PSNR, the lowest MSE, where proposed genetic-Salp-

Swarm filter achieved PSNR (54.84967, 51.98685, 43.57169, 45.4709),MSE equal(0.99075, 0.997525, 1.14925, 2.218438) Gaussian noise , salt-and-pepper noise , possion noise ,and speckle noise on order. Then in compere the our work with other related work based on RMSE value and PSNR value as shown in table 4.

Table4: Comparison of results between proposed hybrid method and other works as PSNR and RMSE values.

Proposed works	PSNR	Proposed works	PSNR	Proposed works	PSNR
Kota NS, et al [19]	14	Mredhula L, et al [22]	25	Umamaheswari J, et al [20]	31
Lalitha YS, et al [23]	28	Chawla P, et al [21]	18	Ali SA, et al [24]	39
Syed AA [25]	29	Ilango G, et al [26]	61.2	Bharathi D, et al [28]	45
Marudhachalam R, et al [27]	59	Marudhachalam R, et al [29]	45	Anisha KK, et al [31]	26
Sharif M, et al [30]	22.54	Yousefi Moteghaed, N., M. TaSalp-Swarmabaeefar, and A. Mostaar [5]	59	Rai, Hari [32]	24.50
Saraiva, A. A., et al [4]	35.76	PRPOSED METHOD Genetic-SALP-SWARM	75.20828		

5. Conclusions

Quantitative and statistical measures as well as image visual quality are used to measure the proposed denoising algorithms' performance. In this paper, we presented a novel method through application a hybrid of two algorithm (genetic algorithm) and (Salp-Swarm algorithms) as a denoising the medical image. In this study, salt-and-pepper noise, possion noise, speckle noise, and gussain noise are used to corrupt the medical images with the noise variances of 0.1,and 0.4 then the proposed method was used to denoise these images. A comparison is made to the result with Wiener filter, Gaussian filter, Median, filters, bilateral filter. Finally, the results of the proposed algorithm are optimum results, when compared with the other conventional filters that were used to denoise medical images. The output from proposed method contains a higher SSIM value higher PSNR value comparing to the other techniques that were used. The results of simulation also revealed that genetic-Salp-Swarm algorithm presented optimum result at a higher level of noise variance. The hybrid GSSA model was applied on medical noisy images and the performances have been determined by the statistical analyses such as PSNR values are gotten (54.84967, 51.98685, 43.57169, 45.4709),MSE equal(0.99075, 0.997525, 1.14925, 2.218438) Gaussian noise, salt-and-pepper noise, possion noise,and speckle noise on order.

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