Hybrid Genetic Algorithm with Filters to Image Enhancement

Baydaa S Bhnam
baydaa_sulaiman@uomosul.edu.iq
College of Computer Sciences and Mathematics
University of Mosul

Received on: 14/10/2012 **Accepted on: 30/01/2013**

ABSTRACT

Image enhancement is a useful and necessary part of image processing and its analysis. The quality of an image could be corrupted by different kinds of noises, added due to the undesired conditions or during the transmission.

In this paper, a **Hybrid Genetic Algorithm with Filters** (**HGAF**) is suggested for the removing of impulse noise from digital images. The new suggested algorithm **HGAF** uses popular (mean , median and min-max filters) and other proposed filters as fitness function for it in order to design eight proposed genetic filters. These eight proposed genetic filters are applied on several gray images corrupted by two types of noise (salt-and-pepper and gaussian noises) with different levels for comparison and to show the effectiveness of them by using the Peak Signal to Noise Ratio (PSNR) and Root Mean Square Error (RMSE). Also, proposed two methods of parents selection to compare between them and types of crossovers and mutations that are used.

Keywords: Image Enhancement**,** Genetic Algorithm, Filters, Noises, Digital Images.

خوارزمية جينية مهجنة مع المرشحات لتحسين الصورة

بيداء سليمان بهنام

كلية علوم الحاسبات والرياضيات، جامعة الموصل

تاريخ استلام البحث: 2012/10/14 **تاريخ قبول البحث: 2013/01/30**

الملخص

ان تحسين الصور جزء مهم وضروري في معالجة الصور وتحليلها. حيث تتشوه الصور بأنواع مختلفة من الضوضاء ويضاف تحت شروط غير مرغوبة او خلال النقل.

في هذا البحث تم اقتراح خوارزمية جينية مهجنة مع المرشحات HGAF لإزالة الضوضاء من الصور الرقمية. تستخدم الخوارزمية المقترحة الجديدة HGAF مرشحات معروفة (مرشح المعدل، الوسيط والتصغير والتكبير) ومرشحات مقترحة اخرى كدالة هدف لهذه الخوارزمية من اجل تصميم ثمانية مرشحات جينية مقترحة. تم تطبيق هذه المرشحات الجينية المقترحة الثمانية على عدة صور ذات تدرج رمادي شوهت بنوعين من الضوضاء (ضوضاء حبات الملح والفلفل وكاوس) وبنسب مختلفة وتم إجراء مقارنة بين هذه المرشحات لمعرفة اكفأها باستخدام PSNR وRMSE. ايضا تم اقتراح طريقتين لاختيار الاباء للمقارنة بينهم وبين انواع التداخل والطفرات المستخدمة.

الكلمات المفتاحية: تحسين الصورة، الخوارزمية الجينية، المرشحات ، الضوضاء، الصور الرقمية.

1. Introduction

In the last few years, Evolutionary Computation (EC) solutions[8],have been applied to solve difficult optimization problems via simulated evolution. By repeatedly utilizing selection and reproduction principles to the population of individuals representing solutions to the problem , the evolutionary techniques evolve a satisfactory solution quickly and efficiently. Therefore, EC tools find applications in many problems ranging from telecommunication networks[3], to fuzzy learning[21], to modeling, and data mining[6], as well as image processing problems mostly related to gray-scale restoration[10],feature extraction, and coding. In this study, we intend to use genetic algorithm (GA) in image filtering and enhancement applications. This choice is reasonable due to the fact that: (i) the intention of this experimentation is to obtain the globally optimal setting of the directional processing based vector filtering scheme considered, (ii) GAs are relatively easy to implement, (iii) the optimization problem defined over the vectorial inputs is complex,and (iv) GAs work well in noisy conditions[16]and[19].

Digital images are prone to impulse noise as a result of errors in the image acquisition , transmission , sensing and storage etc. Noise significantly degrades the image quality and cause great loss of information details in the image; thus, denoising is an essential step to improve the image quality. Image denoising has been widely investigated as an initial image processing method during the past four decades[18]. Random variations in the sensor readings make the recorded values different from the ideal ones, introducing errors and undesirable side effects in the subsequent stages of the image processing process[16]. These errors will appear on the image output in different ways depending on the type of disturbance in the signal. Image Noise is classified as Amplifier (Gaussian), Salt(maximum)-and-pepper(minimum)(Impulse),Shot , Quantization (uniform),Film grain, on-isotropic, Speckle(Multiplicative) and Periodic noise[13]and[17].

2. Related work

Various filtering techniques have been proposed over the year, for removing impulse noise. It is well-known that linear filters could produce serious image blurring hence, non-linear filters have been widely exploited due to their much improved filtering performance, in terms of impulse noise attenuation and edge/details preservation[1]. Sandra S.N. and Ivan S.N.(2007)[22] proposed Partition Based Median (PBM) filter using genetic algorithm in training have demonstrated results in noise suppressing based on median filtering. With PBM filter, at each location, observed vector is classified into one of M exclusive partitions, and a particular filtering operation is then activated. Optimal weighting vector of each partition is derived by using genetic algorithm in training the filter over a reference image. The values of SNR of filtering Lena and cameraman images are corrupted by 20%Gaussian noise are 27.71% and 25.57% respectively .Jin H.H., sung B.C.and Ung K.C.(2009)[14]proposed a method that uses (GA) to determine composite filters that remove different levels of impulse noise from an image. In these methods, the GA considers a set of possible filter combinations of a particular length, selects the best combinations among them according to a fitness value assigned to each combination based on a fitness function. Anisha K.K. and Wilscy M.(2011)[2] proposed a technique that used Fuzzy Genetic Algorithm(FGA) to find the optimal composite filters for removing all types of impulse noise from medical images without using deep knowledge about noise factors. Geoffrine J.M.C. and Kumarasabapathy N.(2011)[7] presented a new Decision Based median filtering algorithm to replace the impulse noise corrupted pixel by the median of the pixel scanned in four directions. The value of PSNR(dB) of cameraman image corrupted by 95% salt-and-pepper noise is PSNR=20.3. Vadivu S.and Jeevaraj E.(2011)[23] proposed Adaptive PDE-based Median Filter (APM Filter) to suppress the high-density fixed-value impulse noise. The value of PSNR(dB) of Lena image corrupted by 90% salt-and-pepper noise is 17.4%. Bhnam,B.S.(2011)[5] proposed genetic filters which are applied on several real images contaminated by two types of noise with different levels. The results show that the fifth genetic filter that depends on the median filter as an objective function and heuristic crossover and adding and subtracting mutation, gives the best results with RMSE=15.7243%and PSNR=24.1646% for Lena.bmp image and with RMSE=8.6197% and PSNR=29.4210 % for girl.png image when add 0.05 salt-and-paper noise. Gupta S. ,Kumar R. and Panda S.K.(2012)[9] use PSNR as a fitness function of genetic algorithm to develop hybrid filter which uses various smoothing filters (both linear and non-linear) in a particular sequence to give an output as improved image with noise reduced.

The objective of this study is to present a new proposed **Hybrid Genetic Algorithm with Filters** (**HGAF**) to remove the impulse noise from digital images. The HGAF uses popular (such as mean[9] , median[4] and min-max filters[15]) and others proposed filters as fitness function of it in order to design eight proposed genetic filters. These eight proposed genetic filters are applied on several gray images corrupted by two types of noise (salt-and-pepper and gaussian noises) with different levels for comparison and to show the effectiveness of them using the Peak Signal to Noise Ratio (PSNR) and RMSE.

This work is organized as follows: Section 3 deals with proposed Hybrid Genetic Algorithm with Filters (HGAF) for de-noising in the images. In section 4, finds fitness function of HGAF in order to design proposed genetic filters. Experimental results in Section 5. The results of filters[5] after and before developed them by HGAF is presented in Section 6. Section 7 shows the results of popular and proposed filters, but without applying HGAF. Section 8 puts forward the conclusions drawn by this paper and Future Research.

3. The Hybrid Genetic Algorithm with Filters (HGAF)

The HGAF has several fitness functions for removing noise from the image. These fitness functions are popular filters (mean , median , min-max filters) and other proposed filters(that will be explained later) in order to design eight proposed filters for removing noise from images. These genetic filters different from [5] about execute GA over all image as well as window. Also, proposed two methods of parent selected rather than parent selection randomly. These proposed genetic filters have been implemented by using MATLAB 7.10.0(R2010a). The performance of these proposed genetic filtering is analyzed and discussed. The simple and widely used objective image quality metrics are Root Mean Square Error (RMSE) and Peak Signal-to-Noise Ratio (PSNR) [11]and[12]:

$$RMSE = \sqrt{\frac{1}{\mathrm{M*N}}\sum_{r=0}^{M-1}\sum_{c=0}^{N-1}\left[\mathrm{Im}_{new}(r,c)-\mathrm{Im}_{old}(r,c)\right]^2} \qquad \ldots(1)$$

$$PSNR = 10\log10(\mathrm{L}\ \ -1)\verb|^|2/\frac{1}{\mathrm{M*N}}\sum_{r=0}^{M-1}\sum_{c=0}^{N-1}\left[\mathrm{Im}_{new}(r,c)-\mathrm{Im}_{old}(r,c)\right]^2 \qquad \ldots(2)$$

Here Im_{old}(r,c) is the original image , Im_{new}(r,c) is an enhanced image, L is 255 and M and N are the total number of pixels in the horizontal and the vertical dimensions of the image.

The Steps of the HGAF as follows:

Step 1) Read original image and then add noise to it.
Step 2) Select a two dimensional window P of size 3×3. (consider each pixel in P as chromosome).
Step 3) Compute the fitness function for the window P using one of popular or proposed filters.
Step 4) Select the parent using one of the proposed methods:

- ***Method 1*** : Select parent closer to the original pixel.
- ***Method 2*** : Select parent closer to original window median.

Step 5) Apply crossover between fitness value and each point in window P and, then apply mutation.
Step 6) Compute RMSE of resulting window. Repeat steps from 3 to 6 until the stopping criterion is achieved. The stopping criteria taken is: optimum found or no increase in quality for 50 generations of window.
Step 7) Select the window that minimum RMSE and put it in an array (B). Repeat steps from 2 to7 until all the windows in the entire image are processed.
Step 8) Compute RMSE and PSNR of the resulting image in B. Repeat Steps from 2 to 8 until the stopping criterion is achieved. The stopping criteria taken is: optimum found or no increase in quality for 50 generations of image.

Fig. 1 shows the flow control of the HGAF. Firstly, read the original image Im , corrupted image K and then, select a window P of size 3×3. After that, compute fitness function for the window P using one of the popular (mean, median and min-max filters) or proposed filters(that will be explained later). At each time, new two points are created in order to find new window by the crossover between each pixel in a window and the fitness value instead of each two pixels in a window that is used in [5]. Then, one of the pixels is selected using one of the proposed selection methods (select pixel closer to the original pixel or closer to original window median) instead of random selection used in[5] , and apply Mutation to avoid the local minima trapping of the algorithm. The RMSE is computed for the window. After the completion of the first iteration for the window, new window is created and the process continues until the stopping criterion is achieved. Then, a window that minimum RMSE is selected among 50 generation for window and put it in the array B. Repeat this process for each window until all the windows in the entire image are processed , then RMSE and PSNR are computed for the processed image. After the completion of the first iteration for the image , repeat this process for each window until the stopping criterion is achieved (number of generation for image) or old RMSE equal new RMSE (for the image) or old PSNR equal new PSNR. Finally , the image that minimum RMSE and maximum PSNR showed among 50 generation for image. This is another difference from [5] about execute the GA over the image as well as window.

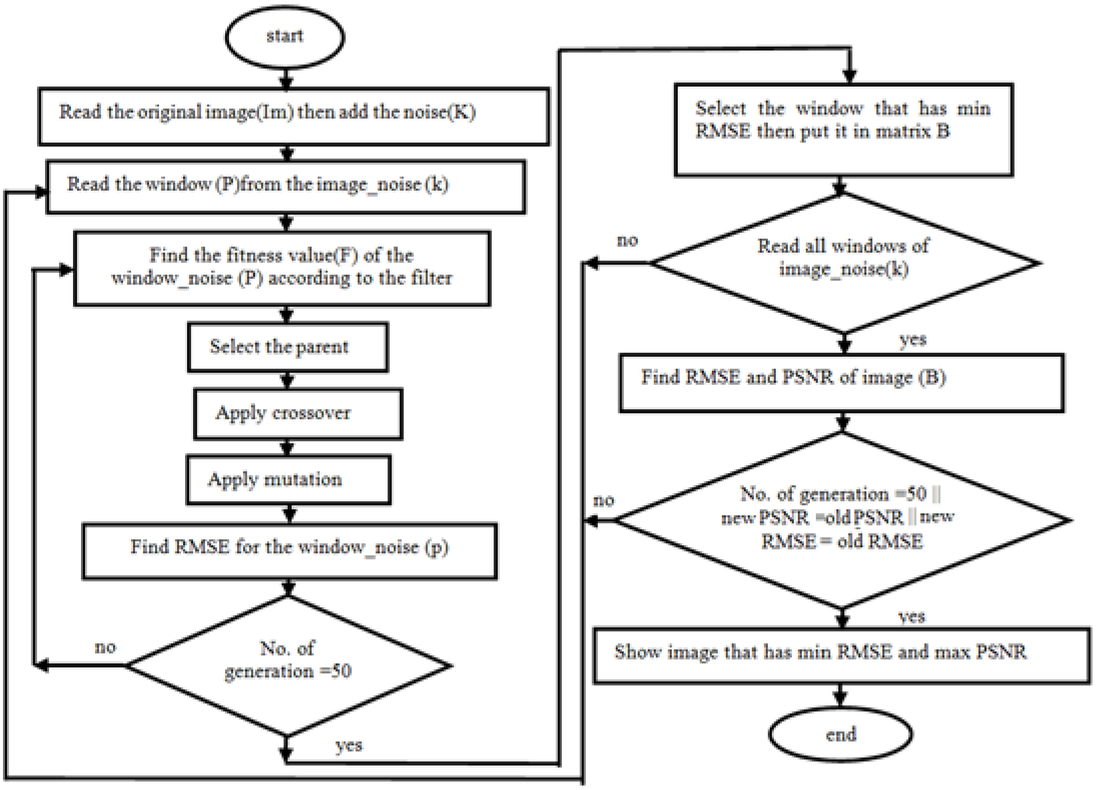

Figure (1):Flow control of the Hybrid Genetic Algorithm with Filters HGAF

4. Find Fitness Function of HGAF In order to Design Proposed Genetic Filters

The HGAF is hybrid with many filters most of them popular and others proposed. These filters are used as fitness function of HGAF. The popular filters are used mean, median , and min-max filters , after hybrid them with HGAF called: Genetic mean filter , Genetic median filter and Genetic min-max filter respectively. The proposed filters are elucidated as follows:

- **Proposed Genetic Mean Filter**

Assume that the pixel being processed is Px and the window_noise is P as 3*3 from the image _noise K. In this proposed filter, Px will be replaced by the mean of the subset of the sorted window Sw according to the conditions that are early determined. Fig.2 shows the proposed genetic mean filter to find the fitness value. The algorithm of this filter to find the fitness value F for window P as follow:

```
The algorithm of the proposed genetic mean filter:
Begin
Px = P(5) ;
Sw  = Sort the window_noise (P)
Find fitness(F) for window(P) as the following:
Case: Px > max(P) ; then F is the mean of last three pixel of Sw as :  F=(Sw (7)+Sw (8)+ Sw (9))/3
Case: Px < min(P) ; then F is the mean of first three pixel of Sw as :  F=( Sw (1)+Sw (2)+Sw (3))/3
Case: median(P) < Px <=max(P)                                           F=(Sw (6)+Sw (7)+Sw (8))/3
Case: min(P) <= Px< median(P)                                           F=(Sw (2)+Sw (3)+Sw (4))/3
otherwise                                                               F= P(5)
end
```

Where P is the window_noise as 3*3 , Px is the pixel being processed , F is the Fitness value , Sw is the window_noise 3*3 after been sorted ascending , max(P) is the maximum pixel of P , min(P) is the minimum pixel of P and median(P) is the median pixel of P.

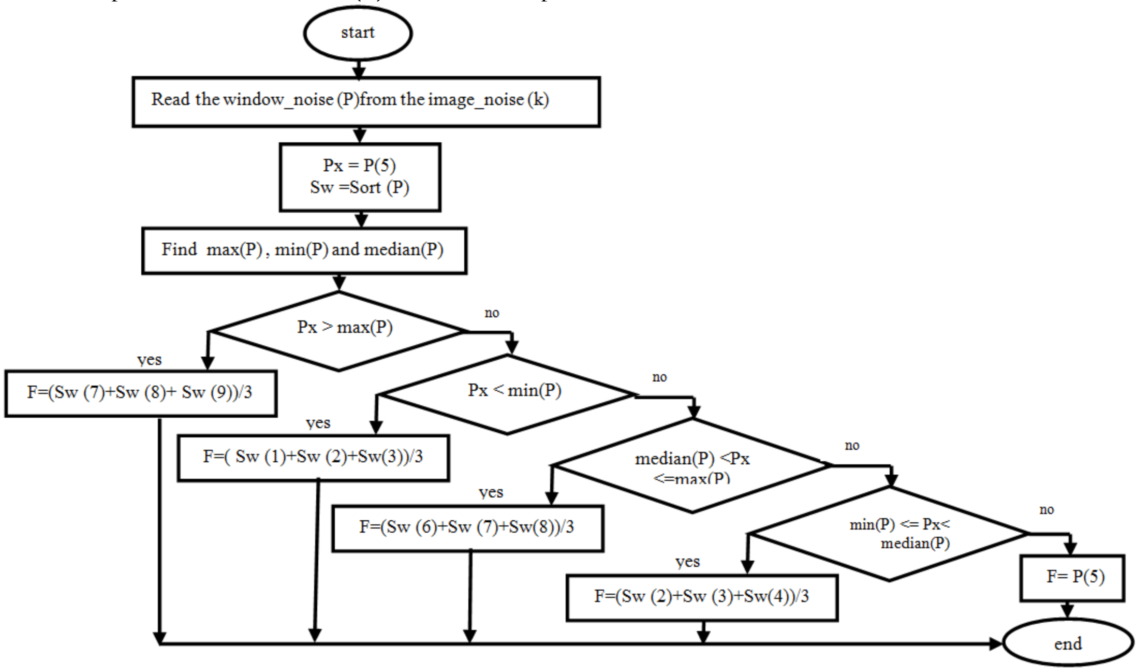

Figure (2): Flow chart to find the fitness value(F) of the window_noise (P) according to the proposed genetic mean filter.

- ## First Proposed Genetic Median Filter

In this proposed filter, instead of replaced Px with mean , here it will replaced by the median of the subset of the sorted window Sw according to the conditions that are early determined. The algorithm of this filter is is explained below:

The algorithm of the first proposed genetic median filter:
Begin
Px = P(5)
Sw = Sort window (P)
Find fitness(F) for window(P) as the following:

Case: Px > max(P)	F=median(Sw (7),Sw (8), Sw (9))
Case: Px < min(P)	F=median(Sw (1),Sw (2),Sw (3))
Case: median(P) < Px < max(P)	F=median(Sw (6),Sw (7),Sw (8))
Case: min(P) < Px < median(P)	F=median(Sw (2),Sw (3),Sw (4))
Otherwise	F= median(P)

end

- ## Second Proposed Genetic Median Filter

The idea of this filter is same as of the first proposed genetic median filter but different of it by first two conditions to find the fitness value and as follows:

Case: Px > max(P)	F= max(P)
Case: Px < min(P)	F=min(P)

- ## First Proposed Genetic Midrange Filter

This proposed filter use the midrange metric [20]to find the fitness value of the window P. The algorithm of this filter is explained below:

The algorithm of the first proposed genetic midrange filter:
Begin
Find fitness(F) for window(P) as the following:
F=(max(P)+min(P))/2
end

- **Second Proposed Genetic Midrange Filter**

Also, this filter uses midrange metric but, for sorted window after first and last pixel of it are excepted. This algorithm is as follows:

The algorithm of the second proposed genetic midrange filter:

Begin
Sw = Sort window (P)
Find fitness(F) for window(P) as the following:
Case: Px > max(P)   F= max(P)
Case: Px < min(P)   F=min(P)
Otherwise   F=(Sw (3)+Sw (7)) /2
end

5. Experimental Results

The eight proposed genetic filters have been tested on images belonging to different types. Lena.bmp (256×256) , Flower.jpg (128×128) , Girl.png (416×512) and cameraman.tif (256×256) are gray-scale images. These images are of different sizes and corrupted by two different types of noises : salt-and-pepper and gaussian noises at different noise densities 0.05 and 0.1. Tables 1, 2 ,3 and 4 show the values of PSNR and RMSE of these filters when apply the first method of parents selection closer to original pixel , arithmetic crossover and bit inverse mutation.

Table(1): Results of Genetic Filters (Arithmetic Crossover and Bit Inverse Mutation) when apply Parents Selection Method closer to original pixel with adding 0.05 salt & pepper noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	10.1286	28.0198	9.9728	28.1545	5.9783	32.5992	14.1149	25.1373
Proposed genetic mean filter	8.8288	29.2128	7.1453	31.0504	**4.8966**	**34.3328**	12.4685	26.2145
Genetic median filter	8.7121	29.1702	7. 6697	30.4352	4.9703	34.2276	12.4755	26.2097
First proposed genetic median filter	8.7793	29.2616	7.4775	30.6557	4.9227	34.2990	12.3153	26.3219
Second proposed genetic median filter	8.8752	29.2755	7.2960	31.0291	**4.8906**	**34.3435**	12.5401	26.1648
Genetic min-max filter	21.8617	21.3371	24.0658	20.5028	11.5986	26.8427	23.9634	20.5398
First proposed genetic midrange filter	18.3924	22.8380	20.6779	21.8207	15.5941	24.2716	23.6914	20.6390
Second proposed genetic midrange filter	11.3045	27.0657	11.5724	26.8624	6.4541	31.9341	16.1548	23.9648

Table(2): Results of Genetic Filters (Arithmetic Crossover and Bit Inverse Mutation) when apply Parents Selection Method closer to original pixel with adding 0.1 salt & pepper noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	10.7286	27.5200	11.1344	27.1975	6.8475	31.4201	16.6539	23.7005
Proposed genetic mean filter	9.2014	28.8537	8.6873	29.9331	5.2196	33.7781	13.1699	25.7391
Genetic median filter	9.3488	28.7157	8.1275	29.3516	5.2201	33.7772	13.0177	25.8401
First proposed genetic median filter	9.3707	28.6953	8.1485	29.9092	5.2114	33.7917	13.2328	25.6978
Second proposed genetic median filter	9.3300	28.7332	8.5527	29.4887	**5.1800**	**33.8441**	13.2119	25.7115
Genetic min-max filter	23.6167	20.6664	33.7000	17.5782	9.9353	28.1872	30.9108	18.3286
First proposed genetic midrange filter	19.7313	22.2277	23.2641	20.4054	18.7181	22.6856	26.1207	19.7911
Second proposed genetic midrange filter	10.3883	27.7999	10.2055	27.9541	6.7640	31.5267	14.4331	24.9436

Table(3): Results of Genetic Filters (Arithmetic Crossover and Bit Inverse Mutation) when apply Parents Selection Method closer to original pixel with adding 0.05 gaussian noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	13.8403	25.9593	14.9385	24.8931	9.7134	28.3836	16.3376	23.8670
Proposed genetic mean filter	17.8440	23.1010	17.3012	23.3693	16.2510	23.9132	19.8063	22.1947
Genetic median filter	17.7602	23.1418	17.3157	23.3620	16.3332	23.8694	19.7047	22.2394
First proposed genetic median filter	17.7089	23.1670	17.2591	23.3904	16.2141	23.9330	19.7179	22.2336
Second proposed genetic median filter	17.8375	23.1041	17.2577	23.3911	16.2707	23.9027	19.7387	22.2244
Genetic min-max filter	22.3160	21.1585	22.1364	21.2286	16.2470	23.9154	23.3000	20.7837
First proposed genetic midrange filter	13.3629	25.6128	14.1353	25.5166	**8.5388**	**29.5028**	16.2376	23.9070
Second proposed genetic midrange filter	14.3421	24.9986	14.2793	25.1222	12.0712	26.4958	17.3727	23.3334

Table(4): Results of Genetic Filters (Arithmetic Crossover and Bit Inverse Mutation) when apply Parents Selection Method closer to original pixel with adding 0.1 gaussian noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	18.4188	22.8256	18.6634	22.7110	16.6345	23.7106	21.4230	21.5132
Proposed genetic mean filter	27.6486	19.2973	27.1737	19.4478	26.8068	19.5659	28.9469	18.8988
Genetic median filter	27.7170	19.2759	27.4755	19.3519	26.7587	19.5815	28.9850	18.8873
First proposed genetic median filter	27.7512	19.2652	27.4644	19.3554	26.8371	19.5561	28.9283	18.9044
Second proposed genetic median filter	27.6318	19.3026	27.8239	19.2424	26.7701	19.5778	28.9943	18.8845
Genetic min-max filter	27.9281	19.2100	29.5877	18.7086	20.8256	21.7588	30.7507	18.3737
First proposed genetic midrange filter	16.6645	23.6950	18.3648	22.8511	**13.2426**	**25.6913**	21.2963	21.5647
Second proposed genetic midrange filter	22.0168	21.2757	22.1833	21.2103	20.9825	21.6937	24.2764	20.4271

Tables 5,6,7 and 8 show the values of PSNR and RMSE when apply the second method of parents selection closer to original window median , same type of crossover and mutation and corrupted these images by 0.05 and 0.1 salt-and-pepper noise and Gaussian.

Table(5): Results of Genetic Filters (Arithmetic Crossover and Bit Inverse Mutation) when apply Parents Selection Method closer to original window median with adding 0.05 salt & pepper noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	8.1834	29.8721	6.8370	31.4335	4.8765	34.3686	11.5509	26.8785
Proposed genetic mean filter	7.8656	30.2437	6.3039	32.1386	4.1032	35.8683	11.5893	26.8496
Genetic median filter	8.3351	29.7126	6.9045	31.3482	4.9990	34.1531	11.7347	26.7414
First proposed genetic median filter	7.8182	30.2686	6.1833	32.3064	4.1412	35.7883	11.5377	26.8884
Second proposed genetic median filter	7.8200	30.2666	6.0612	32.4796	**4.0164**	**36.0540**	11.5036	26.9115
Genetic min-max filter	13.4554	25.5529	16.4314	23.8173	7.0887	31.1194	20.3737	21.9494
First proposed genetic midrange filter	15.0881	24.5581	16.9458	23.5495	14.7382	24.7619	18.8795	22.6110
Second proposed genetic midrange filter	7.9380	30.1366	6.3237	32.1114	4.4210	35.2204	11.4448	26.9587

Table(6): Results of Genetic Filters (Arithmetic Crossover and Bit Inverse Mutation) when apply Parents Selection Method closer to original window median with adding 0.1 salt & pepper noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	8.9821	29.0632	8.0354	30.0307	5.9371	32.6594	12.1966	26.4060
Proposed genetic mean filter	8.4254	29.5700	6.8720	31.3891	4.3070	35.4474	12.1649	26.4286
Genetic median filter	8.4749	29.2363	7.9497	30.1238	5.2126	33.5222	12.4801	26.2064
First proposed genetic median filter	8.2360	29.8165	7.3188	30.8420	4.3676	35.3260	12.3008	26.3321
Second proposed genetic median filter	8.8018	29.7113	7.3632	30.7894	**4.2831**	**35.4957**	12.2902	26.3397
Genetic min-max filter	14.6285	24.8268	17.1880	23.4263	9.6898	28.4045	21.9497	21.3022
First proposed genetic midrange filter	18.3303	22.8674	20.4284	21.9261	18.0466	23.0029	20.7982	21.7703
Second proposed genetic midrange filter	8.6747	29.3657	7.5194	30.6071	5.4560	33.3933	12.0309	26.5249

Table(7): Results of Genetic Filters (Arithmetic Crossover and Bit Inverse Mutation) when apply Parents Selection Method closer to original window median with adding 0.05 gaussian noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	11.2991	27.0699	10.2814	27.8897	9.3407	28.7232	13.9085	25.2652
Proposed genetic mean filter	17.5843	23.2283	17.0502	23.4962	15.9309	24.0860	19.3453	22.3993
Genetic median filter	16.5435	23.7582	16.2113	23.9345	15.1108	24.5451	18.6007	22.7402
First proposed genetic median filter	17.6711	23.1856	16.9178	23.5639	15.9530	24.0740	19.2896	22.4243
Second proposed genetic median filter	17.6047	23.2182	17.0569	23.4928	15.9652	24.0673	19.3128	22.4139
Genetic min-max filter	20.7287	21.7994	20.2403	22.0065	17.2702	23.3849	20.9837	21.6932
First proposed genetic midrange filter	9.7490	28.3516	9.1837	28.8704	**7.3681**	**30.7837**	12.8914	25.9248
Second proposed genetic midrange filter	13.0488	25.8194	12.2525	26.3663	11.4783	26.9333	15.4458	24.3546

Table(8): Results of Genetic Filters (Arithmetic Crossover and Bit Inverse Mutation) when apply Parents Selection Method closer to original window median with adding 0.1 gaussian noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	17.7095	23.1667	17.1011	23.4703	16.8950	23.5756	19.6339	22.2707
Proposed genetic mean filter	27.6352	19.3015	27.1800	19.4458	26.3726	19.7078	28.6329	18.9993
Genetic median filter	25.8607	19.8780	25.7937	19.9005	25.1478	20.1208	27.4052	19.3741
First proposed genetic median filter	27.5812	19.3185	27.3939	19.3777	26.4041	19.6974	28.6926	18.9754
Second proposed genetic median filter	27.6135	19.3084	27.3763	19.3833	26.4849	19.6708	28.6509	18.9381
Genetic min-max filter	25.5581	19.9802	27.8815	19.2245	26.5049	19.6408	28.7115	18.9639
First proposed genetic midrange filter	14.0050	25.2052	13.3167	25.6429	**12.7254**	**26.0371**	16.5894	23.7342
Second proposed genetic midrange filter	21.2543	21.5819	20.9059	21.7254	20.3734	21.9495	22.5599	21.0640

Tables 9 and 10 show the results when apply the second method of parents selection , heuristic crossover , add and sub mutation and corrupted these images by 0.05 salt & pepper noise and gaussian respectively. Fig.3 show the best results of second proposed genetic median filter and first proposed genetic midrange filter.

Table(9): Results of Genetic Filters(Heuristic Crossover and Add and sub Mutation) when apply Parents Selection Method closer to original window median with adding 0.05 salt & pepper noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	7.4961	30.6341	6.0287	32.5263	3.8975	36.3150	10.9701	27.3266
Proposed genetic mean filter	7.1642	31.3823	6.1238	32.3904	3.7803	36.5803	10.6643	27.7766
Genetic median filter	7.7241	30.3738	6.0778	32.4559	4.1591	36.1789	11.4024	26.9908
First proposed genetic median filter	7.0841	30.4190	5.7375	32.9563	4.0019	36.0854	11.4241	26.9744
Second proposed genetic median filter	6.6439	31.8274	5.2287	33.6691	**3.6354**	**37.1198**	10.2108	27.9750
Genetic min-max filter	9.7647	28.3377	8.5955	28.9709	7.2215	30.9582	12.9714	25.8711
First proposed genetic midrange filter	7.8504	30.2330	6.2474	32.2168	4.4518	35.1600	11.2296	27.2666
Second proposed genetic midrange filter	7.5532	30.5682	5.9907	32.6258	3.9862	36.1236	10.9971	27.0052

Table(10): Results of Genetic Filters(Heuristic Crossover and Add and sub Mutation) when apply Parents Selection Method closer to original window median with adding 0.05 gaussian noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Genetic mean filter	9.4241	28.6460	8.0454	30.0199	7.0732	31.1385	12.2270	26.3844
Proposed genetic mean filter	16.2065	23.9449	14.9517	24.6370	14.4530	24.8559	17.6273	23.1815
Genetic median filter	16.0065	24.0449	14.7742	24.7407	14.3630	24.9859	17.5173	23.2615
First proposed genetic median filter	15.9208	24.0915	14.8995	24.6673	14.2797	25.0364	17.6055	23.2178
Second proposed genetic median filter	15.8111	24.1515	14.9125	24.6598	14.3529	24.9920	17.4864	23.2768
Genetic min-max filter	20.5348	21.8810	19.1091	22.5060	18.4555	22.8083	22.5291	21.0759
First proposed genetic midrange filter	7.5121	30.6156	6.0656	32.4733	**4.1817**	**35.7038**	10.9701	27.3235
Second proposed genetic midrange filter	12.3157	26.3216	11.0692	27.2485	10.5034	27.7042	14.4115	24.9566

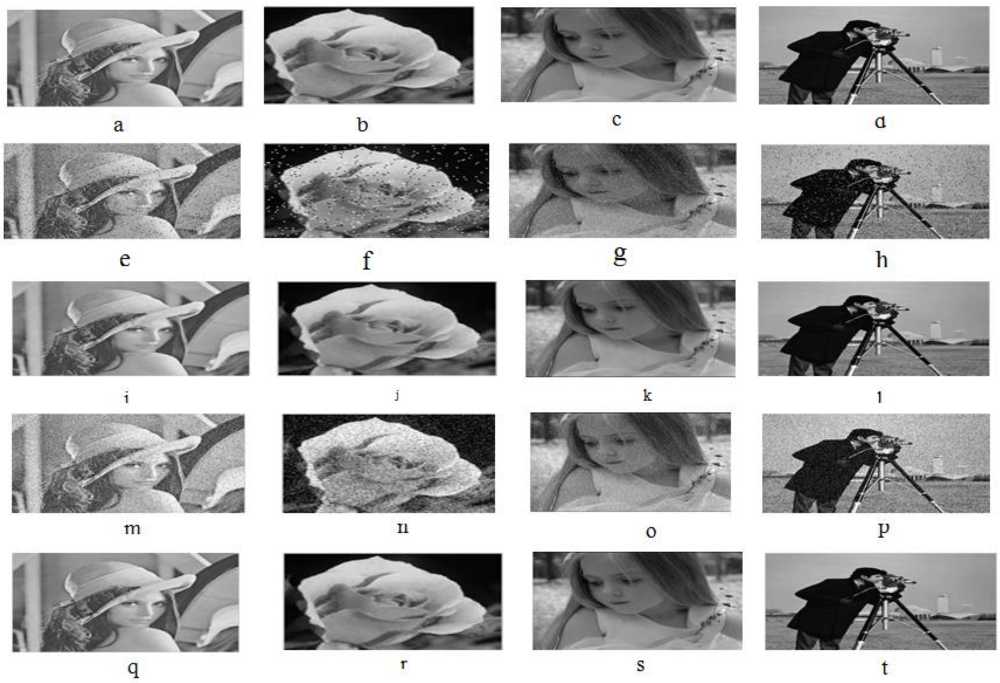

Figure (3): (a,b,c,d) original image. (e,f,g,h) Noise 0.05 salt and pepper image. (i,j,k,l) restored by second suggested proposed median filter. (m,n,o,p) Noise Gaussian image. (q,r,s,t) restored by first suggested proposed midrange filter.

6. Results of Filters [5] After and Before Developed them by HGAF

The filters in [5] have been developed them according to HGAF. Tables 11 and 12 show the results of these filters [5] after developed by HGAF and apply the second method of parents selection. Table 13 shows the results of the best genetic filters according to the [5].

Table(11): Results of Genetic Filters [5] when apply Parents Selection Method closer to original window median with adding 0.05 salt & pepper noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
First genetic filter	7.6211	30.4904	5.8951	32.7210	4.0645	35.9508	11.0557	27.2590
Second genetic filter	7.8412	30.2431	6.4056	31.9996	4.0740	35.9303	11.3209	27.0532
Third genetic filter	7.8862	30.1934	5.9349	32.6625	4.0974	35.8806	11.4959	26.9199
Fourth genetic filter	7.7889	30.3525	5.9107	32.1504	**3.9298**	**36.2434**	11.9842	27.3814
Fifth genetic filter	7.4375	30.6488	5.6800	32.7868	**3.9262**	**36.2462**	11.2275	27.0604
Sixth genetic filter	7.6739	30.4305	5.9480	32.1934	**3.9285**	**36.2457**	11.3450	27.0347

Table(12): Results of Genetic Filters[5] when apply Parents Selection Method closer to original window median with adding 0.05 gaussian noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
First genetic filter	9.4409	28.6306	8.1624	29.8945	7.0858	31.1231	12.3443	26.3015
Second genetic filter	15.8932	24.1066	15.2472	24.4670	14.3330	25.0041	17.8863	23.0804
Third genetic filter	16.0560	24.0180	15.2792	24.4488	14.3794	24.9760	17.9120	23.0679
Fourth genetic filter	9.3987	28.6694	7.8949	30.1838	7.0036	31.2244	12.2575	26.3627
Fifth genetic filter	15.6111	24.2621	14.2457	25.0571	13.8402	25.3080	17.2644	23.3878
Sixth genetic filter	15.6621	24.2338	14.6664	24.8043	13.8422	25.3067	17.2617	23.3891

Table(13): Results of the best Genetic Filters according to the [5].

IMAGES	Lena.bmp		Girl.png		
FILTERS	RMSE	PSNR	RMSE	PSNR	
First genetic filter	20.0148	22.0750	17.4941	22.8968	*Adding 0.05 gaussian noise*
Fourth genetic filter	20.0805	22.1016	17.6183	22.9115	*Adding 0.05 gaussian noise*
Fifth genetic filter	15.7243	24.1646	8.6197	29.4210	*Adding 0.05 salt & pepper*

7. Results of the popular and proposed filters but without apply HGAF

The mean , median, min-max and proposed filters have been tested on these images but, without HGAF. Tables 14 and 15 show the results of these filters without HGAF .

Table(14):Results of the popular and proposed filters but without apply HGAF when adding 0.05 salt-and-pepper noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Mean filter	13.8549	25.2987	14.5215	24.8906	11.3605	27.0229	16.8242	23.6121
Proposed mean filter	8.6552	29.3853	9.4747	28.5995	5.7046	31.6033	12.5393	25.6745
Median filter	9.9840	28.0863	7.7745	31.5132	6.0343	30.0155	13.6428	24.8097
First proposed median filter	8.8893	29.0165	7.6789	30.4248	5.7002	35.7662	12.5929	25.4918
Second proposed median filter	29.9467	18.6038	34.0187	17.4964	30.8105	18.3568	32.4782	17.8990
Min-max filter	10.8994	27.1789	9.1443	25.0613	8.5577	28.9259	14.6972	23.7692
First proposed midrange filter	38.5114	16.4190	43.3231	15.3964	38.9701	16.3162	43.0043	15.4606
Second proposed midrange filter	9.7307	28.3679	9.9656	28.1608	5.9160	32.6902	13.9029	25.2687

Table(15): Results of the popular and proposed filters but without apply HGAF when adding 0.05 gaussian noise.

IMAGES	Lena.bmp		Flower.jpg		Girl.png		Cameraman.tif	
FILTERS	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR
Mean filter	22.4704	21.0986	22.6779	21.0188	21.7612	21.3771	23.1832	20.8273
Proposed mean filter	22.3535	21.1439	22.6946	21.8471	21.8471	21.3429	23.0623	20.8728
Median filter	18.3641	22.8514	17.6395	23.2011	16.9573	23.5437	19.9604	22.1274
First proposed median filter	21.8583	21.3385	21.8207	21.3534	20.8650	21.7424	23.2772	20.7922
Second proposed median filter	27.3912	19.3786	27.3797	19.3822	27.5456	19.3298	28.1117	19.1531
Min-max filter	22.1953	19.9316	20.5826	21.2292	20.9696	20.5374	23.9456	19.1339
First proposed midrange filter	19.6234	22.2753	22.3371	21.1503	17.7681	23.1380	24.3834	20.3889
Second proposed midrange filter	19.7346	22.2262	21.9548	21.3002	17.8175	23.1139	24.5819	20.3185

8. Conclusions & Future Research

1. The girl.png is suitable for HGAF in comparison with cameraman.tif.
2. Method2 of selection (the parents selection method closer to original window median) gives better results of all filters in comparison with method1(the parents selection method closer to original pixel).
3. The heuristic crossover and add and sub mutation is much suitable than other crossovers and mutations.
4. The filters in [5] after developed by HGAF and apply the second method of parents selection closer to original window give better results in comparison with[5].
5. The ***second proposed genetic median filter*** gives better results as well as the perceived image quality in comparison with other filters and filters in [5] after development by HGAF when the images are corrupted by salt-and-pepper noise. But when corrupted them by gaussian noise , the better is ***first proposed genetic midrange filter***. Experiments conducted show that the HGAF is much better than the popular and proposed filters without HGAF as well as filters in[5] for removing impulse noise from these images along with image detail preservation in terms of PSNR and RMSE . The proposed algorithm is faster since it uses a small window of size 3×3. The success of optimization strongly depends on the chosen parents selection method, crossover and mutation strategies as well as fitness function(selection popular and proposed filters).

   As future work, the proposed method can be used in applications such as impulse noise removal from satellite , medical and color images. Also, corrupt the images with other types of noises with high densitiy and removing impulse noise by the HGAF.

REFERENCES

[1] Aborisade, D.O ,2011," A Novel Fuzzy logic Based Impulse Noise Filtering Technique", International Journal of Advanced Science and Technology Vol. 32,pp.79-88.

[2] Anisha K. K. and Wilscy M.,2011,"Impulse noise removal from medical images using fuzzy genetic algorithm", The International Journal of Multimedia & Its Applications (IJMA) Vol.3, No.4,pp. 93-106.

[3] Arabas, J. and Kozdrowski, S., 2001, "Applying an evolutionary algorithm to telecommunication network design", IEEE Trans Evol Comput 5 , pp.309–322.

[4] Babu K.R.,Rahul L.A., Souri P.V. and Suneetha A.,2011," Image Denoising in the Presense of High Level Salt and Pepper Noise using Modified Median Filter",International Journal of Computer Sci ence & Technology, IJCST Vol.2,pp.180-183.

[5] Bhnam B. S.,2011,"Using Genetic Algorithm to Reduce The Effective Noise on Images", published accepted by A-Rafidain Journal of computer sciences and mathematics on 14/12/2011.

[6] Brameier, M. and Banzhaf, W.,A,2001," comparison of linear genetic programming and neural networks in medical data mining", IEEE Trans Evol Comput 5, pp.17–26.

[7] Geoffrine J.M.C and Kumarasabapathy N.,2011,"study and analysis of impulse noise reduction filters", Signal & Image Processing : An International Journal(SIPIJ) Vol.2, No.1, pp. 82-92.

[8] Goldberg,D. , 2002, "The design of inovation: Lessons from and for competent genetic algorithm", Kluwer Academic Publishers, Boston.

[9] Gupta S., Kumar R., Panda S. K.,2012,"A Genetic Algorithm Based Sequential Hybrid Filter for Image Smoothing",International Journal of Signal and Image Processing ,Vol.1/Iss.4,pp. 242-248.

[10] Hamid, M.S. , Harvey, N.L. , and Marshall, S.,2003, "Genetic algorithm optimization of multidimensional rayscale soft morphological filters with applications in film archive restoration", IEEE Trans Circuits Syst Video Technol 13, pp.406–416.

[11] Horé A. and Ziou D.,2010,"Image quality metrics: PSNR vs. SSIM ", International Conference on Pattern Recognition,IEEE computer society,pp. 2358- 23671.

[12] Ilango G. and Marudhachalam R., 2011,"new hybrid filtering techniques for removal of gaussian noise from medical images", ARPN Journal of Engineering and Applied Sciences ISSN 1819-6608, Vol. 6, No. 2,pp.8-12.

[13] Jayaraj V., Ebenezer D. and Vijayakumar V. R.,2011, "A Noise Free Estimation Switching Median Filter for Detection and Removal of Impulse Noise in Images" ,European Journal of Scientific Research ISSN ,Vol.51No.4,pp.563-81.

[14] Jin H.H., Sung B.C. and Ung K. C.,(2009) “A Novel Evolutionary Method to Image Enhancement Filter Design: Method and Applications”, IEEE Transactions on Systems, Man and Cybernetics-Part B, Cybernetics,Vol. 39,No.6,pp.1446-1457.

[15] Koli M. A.,2012,"Review of Impulse Noise Reduction Techniques", International Journal on Computer Science and Engineering (IJCSE),ISSN : 0975-3397 Vol. 4 No. 02 ,pp. 184-196.

[16] Lukac, R.,Plataniotis, K.N. and Venetsanopulos, A.N., 2005,"Color Image Denoising Using Evolutionary Computation", Wiley Periodicals, Inc., Vol. 15, pp.236–251.

[17] Mythili C. and Kavitha V. ,2011,"Efficient Technique for Color Image Noise Reduction",The Research Bulletin of Jordan ACM - ISWSA; ISSN: 2078-7952, V o l . I I (I I I),pp.41-44.

[18] Pakdelazar, O. and Rezai-rad, G., 2011, "Improvement of BM3d algorithm and employment to satellite and cfa images denoising", International Journal of Information Sciences and Techniques (IJIST) Vol.1, No.3,pp.23-33.

[19] Paulinas M. and Ušinskas A.,2007,"a survey of genetic algorithms applications for image enhancement and segmentation", ISSN 1392 – 124X information technology and control, Vol.36, No.3 ,pp.278-284.

[20] Richard A. J. and Gouri K. B.,2010, "Statistics Principles and Methods ",6th edition, John Wiley & Sons, Inc.

[21] Russo, M.,2000," Genetic fuzzy learning", IEEE Trans Evol Comput4,pp.259–273.

[22] Sandra S.N. and Ivan S.N.,2007,"Application of Genetic Algorithm in Median Filtering", Proceedings of the International Multiconference on ISSN 1896-7094, pp. 127 – 139.

[23] Vadivu S. and Jeevaraj E.,2011,"adaptive PDE-based median filter for the restoration of high-density impulse noise corrupted images", International Journal of Advanced Information Technology (IJAIT) Vol. 1, No.6,pp. 43-51.