Application of Bacterial Foraging Optimisation as a De-noising filter

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***Abstract*— De-noising of image still a concerned for researchers working in this area. It is further challenging in case of medical images mainly images of the internal organs. Various digital filters have been developed and tried by researchers to provide ideal solution in the de-noising of medical images. In the present paper the authors present a Soft Computing approach to de-noise the medical images. Bacterial Foraging Optimisation which is a bio-inspired algorithm is used as filter to de-noise medical images like CT-Scan and MRI of pancreas. The performance metrics like MSE and PSNR are calculated which show that Bacterial Foraging Optimisation can act as potential tool for de-noising images.**

***Keywords*— BFO, cost function, MSE, PSNR, De-noising, Medical image**

I. INTRODUCTION

During image acquisition process due to different processing such as A/D conversion, transmission etc. the digital images gets added with noise. Different types of noises corrupt digital images at different stages of image processing.[1][3] While dealing with medical images, the image gets corrupted by variety of noise mainly from bone, soft tissue, body movement etc. Therefore precautions are taken to reduce the noise to a larger possible extent in the medical images for better diagnosis. However, the demands for noise free image are increasing day by day so is the case for better de-noising filters. Soft Computing techniques in the recent past have been used by researchers either in isolation or in conjunction with Adaptive Median filter or Median filter to de-noise images. In this paper, the authors have presented a technique to de-noise medical images using Bacterial Foraging Optimization technique.

For removing the Gaussian noise, Bacterial Foraging Optimisation is hybridised with Average filter whereas for other noise BFO is applied by hybridising it with Adaptive Median filter. Bacterial Foraging Optimisation developed by Passino in 2002 [8] bio-inspired Optimisation technique that is derived from the food searching process of E. Coli bacteria. As the bacteria travel in slow speed, it gives the capability to search the pixel without jumping or slipping out pixels thus, improving the quality of image. To test the capability of proposed algorithm, medical images like CT-Scan and MRI of pancreas are considered. Self image is also taken to see the performance of algorithm as a de-noising filter.

Along with several digital filtering techniques, Soft computing techniques are gaining importance in de-noising process. Several digital filtering techniques used by researchers to remove Salt &Pepper noise have been published. Progressively determining noisy pixel and removal of noisy pixel by switched median filter used in[10]. Modified Median filter used in [2]. Artificial neural network, Fuzzy logic, Genetic Algorithm, Optimisation techniques such as Particle Swarm Optimisation [4] are some important Soft Computing techniques. PSO is applied to de-noise images[11][12] by optimising cost function as structure of similarity, Bacterial Foraging Optimisation [8], Swine Influenza Model Based Optimisation [9] are some important Soft computing techniques. Researchers used various soft computing techniques and hybrid techniques to de-noise images [1]. In this paper, BFO is used to optimise the output of Adaptive Median filter when images are corrupted with Salt and Pepper noise and output of Average filter is optimized when images are corrupted with Gaussian noise. Experiment is performed on two benchmark images – Lena and Bridge and CT-Scan and MRI of pancreas and image of self.

The paper is organised in following sections. Section II. Presents BFO, Section III. explains the proposed soft filter, BFO Soft Filter for noise removal, Section IV. shows Results and Discussion and Section V. encompasses the Conclusion.

II. BACTERIAL FORAGING OPTIMIZATION

For the completion of paper Bacterial Foraging Optimisation given by Passino is discussed here. Bacterial Foraging Optimisation is based on foraging strategy of E.Coli bacteria. Bacteria move in random direction to search favourable direction of increasing nutrients. Thus, this Optimisation technique is useful when gradient of cost function is not known. Bacterial Optimisation is good because of its less mathematical complexity, convergence, accuracy and wide application. This Optimisation is accomplished in four steps- Chemo-taxis, Swarming, Reproduction and Elimination and Dispersal.

(i) Chemo taxis: Single Chemo-tactic step completes in tumble, run and tumble if nutrient does not increase in the direction of swim and otherwise it is tumble, run(swim) and followed by run (as per defined limit of swim) if concentration of nutrient increases in the direction of swim. A unit walk with random direction represents a Tumble and unit walk with same direction in the last step indicates Run. Mainly foraging completes in Chemo-tactic step.

(ii) Swarming: The cells when stimulated, release an attractant aspirate, which helps them to aggregate into groups and move as concentric patterns of swarms. This helps to achieve global optimum value for cost function. Swarming helps in fast convergence in case of multidimensional cost function.

(iii) Reproduction: After calculating fitness value for each bacteria, reproduction allows the half healthy bacteria (with least cost value) to survive and reproduce. The remaining half unhealthy bacteria die. This step helps in the generation of values of variables which are closer to actual value. Fifty percentage of the population is removed in each state and rest fifty percentage reproduce.

(iv) Elimination and Dispersal: The chemo taxis provides a basis for local search and reproduction speeds the convergence. But to avoid the trap of bacteria in local minimum Elimination –Dispersal is done.

III. BFO AS SOFT FILTER

To test the proposed concept, initially ideal images are corrupted with noise. Then the noisy image is passed through Adaptive Median filter. Now the difference in terms of Mean Square Error between this filtered image and the original image is minimised using BFO. The block diagram of the process is shown Fig. 1

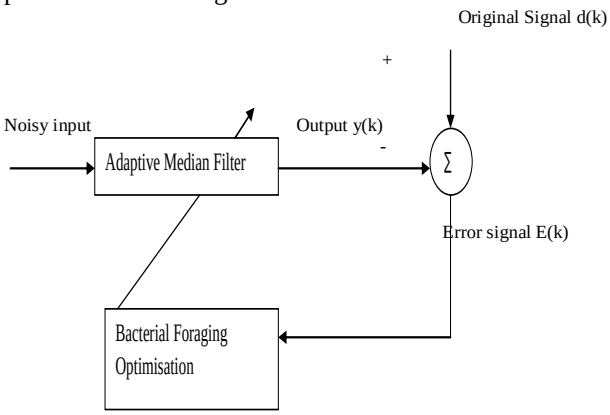


Fig. 1: Block diagram of Soft filter

The original resized images selected for the testing are shown in Fig. 2

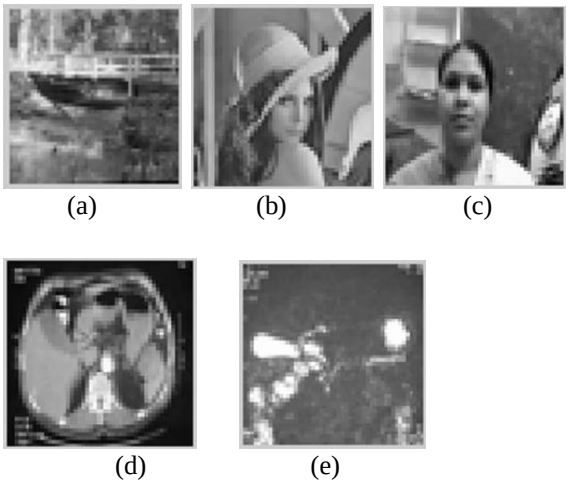


Fig.2: Original resized image (a) Bridge (b)Lena (c) Self (d) CT-Scan of pancreas (e) MR Cholangiopancreatogram

BFO is used to minimize the Mean Square Error between Adaptive Median filter output and target image to restored image which is closer to actual image. Parameters selected to de noise image are-

Number of bacteria in population used for searching (S) = M×N size of image, in this case it is 50×50 (downsized)
Dimension of search space (p) = 1
Number of Chemo tactic steps (Nc) = 2
Number of swimming steps (Ns) = 1
Number of reproduction steps (Nre) = 2
Number of elimination and dispersal (Ned)=2
Probability of elimination and dispersal (ped) = 0.25
Cost function used to minimize using BFO is MSE.

$$\text{MSE} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left(f'(x,y) - f(x,y)\right)^2$$

Where f'(x, y) = filtered output
F(x, y) = target image
Due to pixel –by- pixel operation, f'(x, y) = P(i, j , k ,l) and f(x, y) = R(x, j, k, l)
$J(i, j, k, l) = |P(i, j , k ,l) - R(x, j, k, l)|^2$
Where
P(i, j , k ,l) = location of ith pixel (bacteria) at jth chemo tactic step, kth reproduction step and lth elimination step.
R(x, j, k, l) = location of xth target pixel at jth chemo tactic step, kth reproduction step and lth elimination step.
J(i, j, k, l) = Cost of ith pixel (bacteria) at jth chemo tactic step, kth reproduction step and lth elimination step.

A. Algorithm used for de noising images

For xth target pixel optimization takes in following steps:
Initialize parameters p, S, NC, NS, Nre, Ned, ped, and C(i), i= 1,2,3……S.
C(i) = Step size in the random direction
Step 1: Elimination –dispersal loop :l=l+1
Step 2: Reproduction loop : k=k+1
Step 3: Chemo taxis loop : j=j+1

a) For i=1,2,…….,S, take a chemo tactic step for bacterium i as follows.

b) Let Jlast=J(I,j,k,l)= $| P(i, j , k ,l) - R(x, j, k, l) |^2$

where

P(i, j , k ,l) = location of ith pixel (bacteria) at jth chemo tactic step, kth reproduction step and lth elimination step.

R(x, j, k, l) = location of xth target pixel at jth chemo tactic step, kth reproduction step and lth elimination step.

J(i, j, k, l) = Cost of ith pixel (bacteria) at jth chemo tactic step, kth reproduction step and lth elimination step..

c) Tumble: A random vector Δm(i), m= 1,2,…p, a random number in [-1,1].

d) Move: Let (j+1,k,l)= (j,k,l) + C(i) . results in a step C(i) in the direction of the tumble for bacterium i.

e) Swim:

i. Let m= 0 (counter for swim length).

ii. While m< NS

- Let m= m+1
- If J(i,j+1,k,l) < Jlast ,

Let Jlast = J(i,j+1,k,l) and let Pi(j+1,k,l) + C(i)

And use this Pi(j+1,k,l) to compute the new J(j+1,k,l).

- Else, let m = N_S.

f) Go to next bacteria (i+1) if i≠ S

Step 4: If j < NC, go to step 3.

Step 5: Reproduction:

i) For the given k and l, and for each i= 1,2,……S, let J(i,j,k,l)

ii) The Sr = S/2 bacteria with the highest value of cost function die and other Sr = S/2 bacteria with the best value (least value of cost function) split.

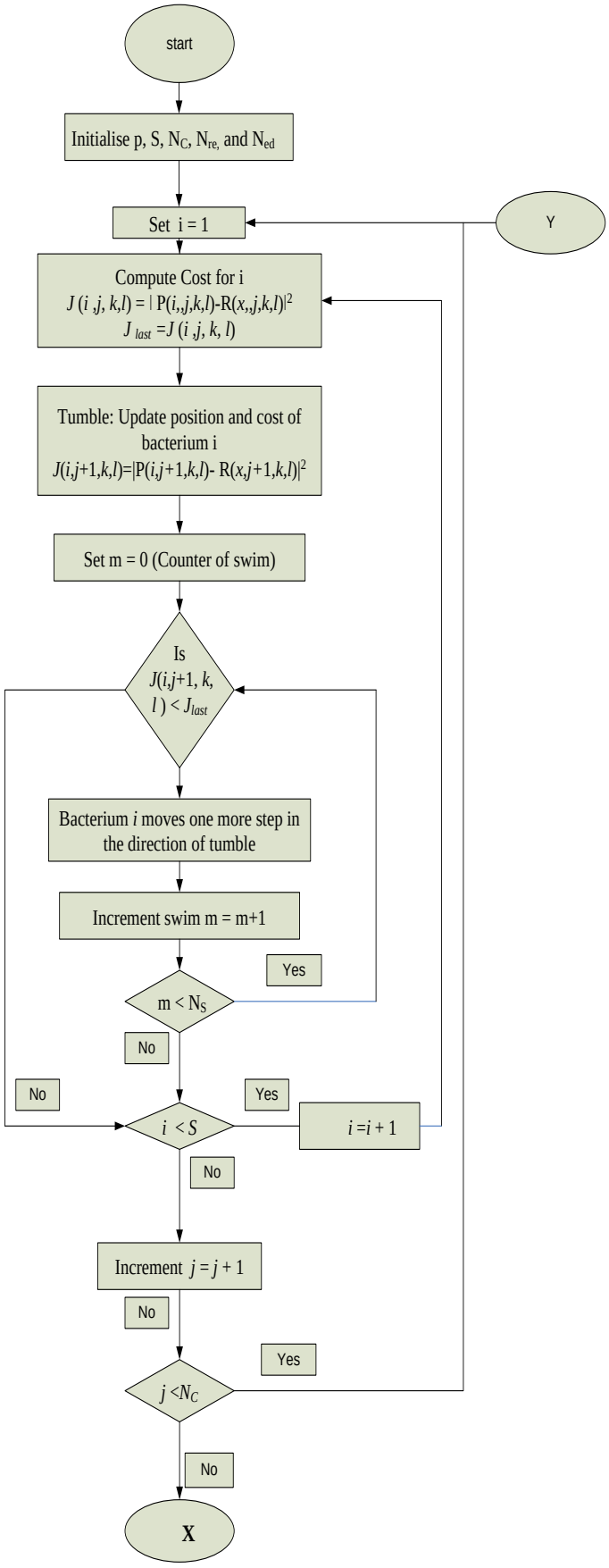
Step 6: If k < Nre, go to step 2.

Step 7: Elimination- dispersal: Eliminate and dispersal each bacterium.

Step 8: If l < Ned , go to the step 1.

Otherwise end.

The flow chart is depicted in Fig. 3



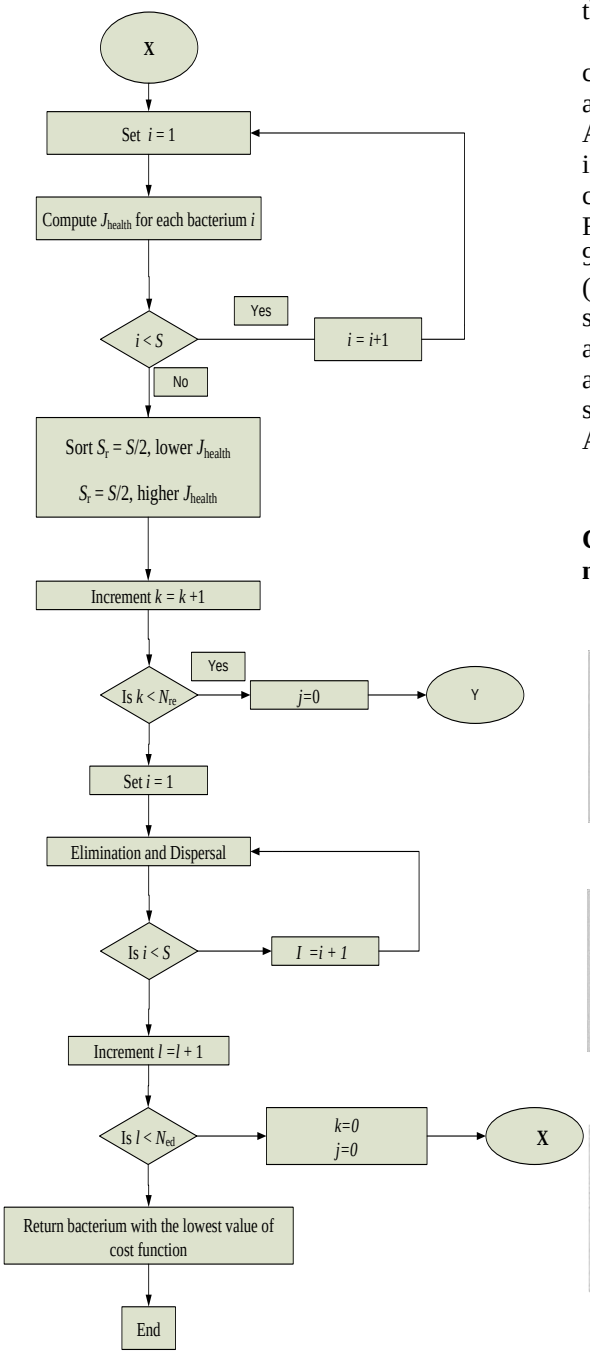


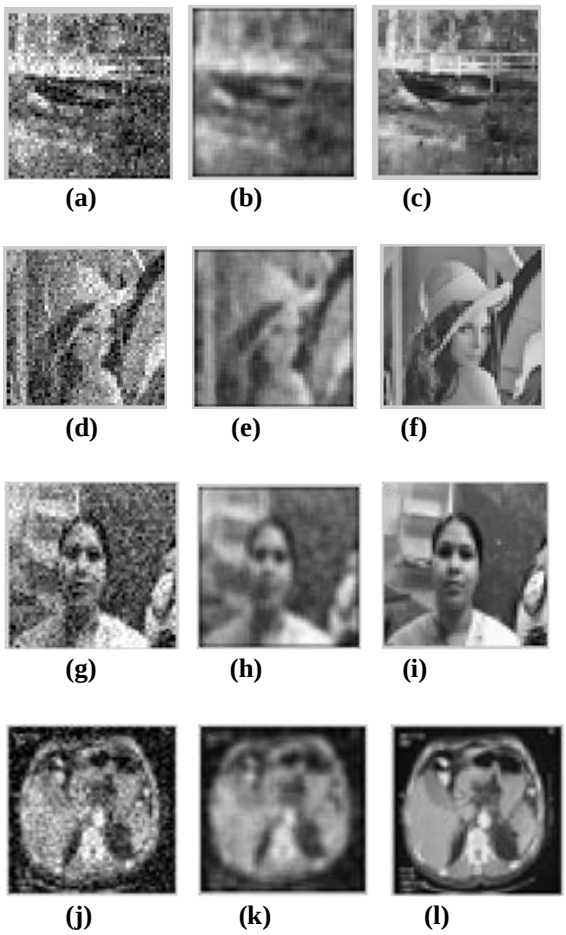
Fig. 3: Flow chart of the proposed algorithm

IV. RESULTS AND DISCUSSION

Benchmark images such as Lena and Bridge are initially considered. To reduce the processing time, the images are downsized to (50×50). Salt and pepper noise with varied noise density 10% to 90% are used. In case of Gaussian noise variance is changed from 0.002 to 0.07. Then medical images like CT-Scan and MRI of pancreas are considered. Pancreas being one of the innermost organs, hence is prone to different types of noise. The original medical image is corrupted with the varied noise density or variance.

Fig.3 and Fig.4 (a)(d)(g)(j)(m) show considered images corrupted with Gaussian noise at Standard Deviation 0.002 and 0.07 respectively, Fig.3 and Fig.4 (b)(e)(h)(k)(n) show Average filtered images, Fig. 3 and Fig.4(c)(f)(i)(l)(o) show images restored after BFO. Table 1 shows MSE and PSNR for considered image for Gaussian noise. Fig.5 and Fig.6(a)(d)(g)(j)(m) show images corrupted with 50% and 90% Salt and Pepper noise respectively, Fig.5 and Fig.6 (b)(e)(h)(k)(n) show AMF image, Fig.5 and Fig.6(c)(f)(i)(l)(o) show the images restored after BFO and Table 2 shows MSE and PSNR for the considered images experimented with Salt and Pepper noise. As seen from the above quality matrices study, BFO outputs is considerably large compared to that of AMF. The quality of image thus is high for BFO filtered case.

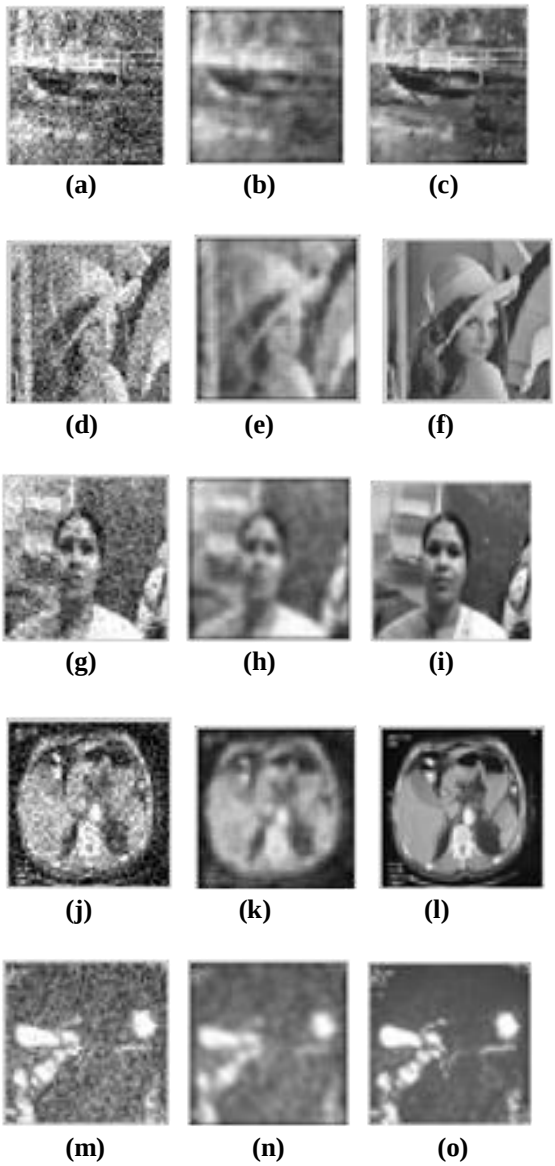
Experimentation with the images of Lena, Bridge, Self, CT-Scan and MRI of pancreas corrupted with Gaussian noise at S.D.= 0.004



(m) (n) (o)

Fig.3: (a)(d)(g)(j)(m) Image corrupted with Gaussian noise at S.D. of 0.004 (b)(e)(h)(k)(n) Average filtered Image (c)(f)(i)(l)(o) Image restored after BFO

Experimentation with the images of Lena, Bridge, Self, CT-Scan and MRI of pancreas corrupted with Gaussian noise at S.D.= 0.07



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

(j) (k) (l)

(m) (n) (o)

Fig.4: (a)(d)(g)(j)(m) Image corrupted with Gaussian noise at S.D. of 0.07 (b)(e)(h)(k)(n) Average filtered Image (c)(f)(i)(l)(o) Image restored after BFO

TABLE I
COMPARISON OF AVERAGE FILTER AND BFO ON THE BASIS OF MSE AND PSNR FOR THE IMAGES, BRIDGE, LENA, SELF CT-SCAN OF PANCREAS AND MR CHOLANGIOPANCREATOGRAM

Image	S.D. (σ)	Average Filter		BFO	
		MSE	PSNR (dB)	MSE	PSNR (dB)
Bridge	0.002	439.5551	21.7007	0.4633	51.4721
	0.004	435.7321	21.7386	0.1705	55.8140
	0.006	435.3541	21.7424	0.1666	55.9141
	0.008	435.5069	21.7409	0.1698	55.8302
	0.01	436.1986	21.7340	0.1720	55.7763
	0.03	468.9167	21.4198	0.2550	54.0654
	0.05	543.4171	20.7795	0.9374	48.4116
	0.07	665.4071	19.8999	01.6022	46.0836
Lena	0.002	432.6510	21.7694	0.0078	69.2283
	0.004	433.2666	21.7633	0.0066	69.9214
	0.006	449.5479	21.6030	0.0237	64.3797
	0.008	428.4987	21.8113	0.0490	61.2274
	0.01	441.1730	21.6847	0.0120	67.3315
	0.03	470.4446	21.4057	0.0095	68.3485
	0.05	541.5641	20.7943	0.0109	67.7562
	0.07	669.1511	19.8756	0.0399	62.1166
Self	0.002	503.4207	21.1115	0.6266	50.1608
	0.004	525.03111	20.9290	0.5953	50.3833
	0.006	539.1716	20.8135	1.2647	47.1110
	0.008	511.9681	21.0384	0.2537	54.0883
	0.01	502.1488	21.1225	0.2879	53.5378
	0.03	550.0545	20.7267	0.4845	51.2775
	0.05	608.4642	20.2885	0.1525	56.2988
	0.07	708.3690	19.6282	1.3943	46.6872
CT-Scan of pancreas	0.002	433.4032	21.7619	0.3397	52.8202
	0.004	437.2765	21.7232	2.1233	44.2765
	0.006	442.1166	21.6754	1.7204	45.7746
	0.008	447.1674	21.6261	0.8296	48.9422
	0.01	441.2470	21.6840	1.8203	45.5294
	0.03	482.1797	21.2987	0.6371	50.0885
	0.05	587.0902	20.4438	0.2155	54.7968
	0.07	740.2602	19.4370	0.1581	56.1416
MRI of pancreas	0.002	319.7177	23.0831	0.0986	58.1911
	0.004	320.0820	23.0782	0.3469	52.7294
	0.006	340.6056	22.8083	0.3461	52.7384
	0.008	319.6388	23.0842	0.2854	53.7384
	0.01	320.4456	23.0733	0.2652	53.8943
	0.03	352.3240	22.6614	0.1384	56.7195
	0.05	437.4703	21.7213	0.0428	61.8198
	0.07	559.7121	20.6512	0.0084	68.8768

Experimentation with the images of Lena, Bridge, MRI ,CT-Scan of pancreas and image of self at 50% Salt & Pepper Noise

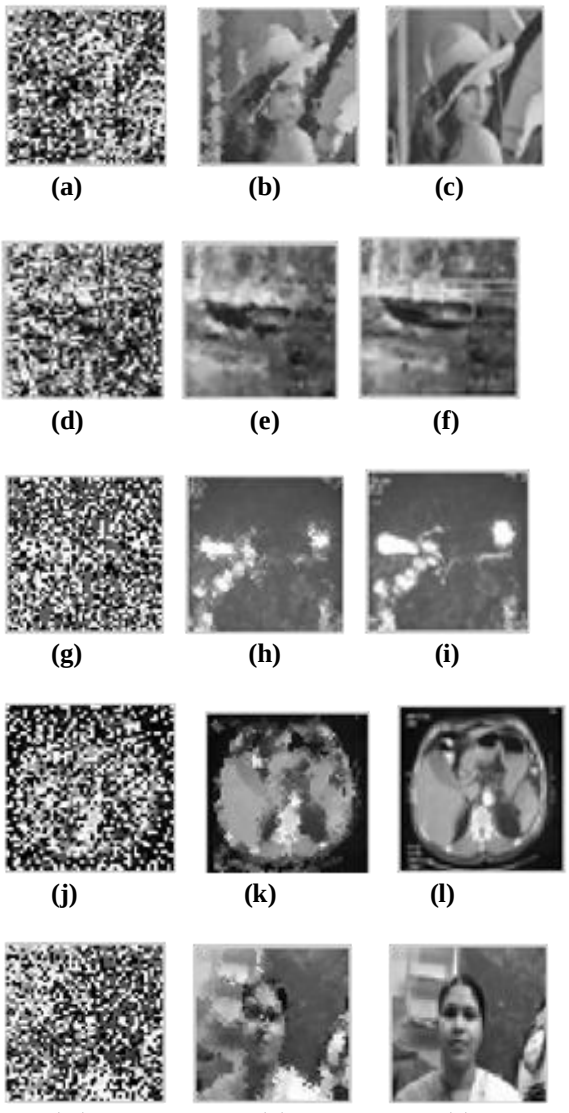


Fig.5: (a)(d)(g)(j)(m) Image corrupted with 50% Salt & Pepper noise (b)(e)(h)(k)(n) AMF Image (c)(f)(i)(l)(o) Image restored after BFO

Experimentation with the images of Lena, Bridge, MRI ,CT-Scan of pancreas and image of self at 90% Salt & Pepper Noise.

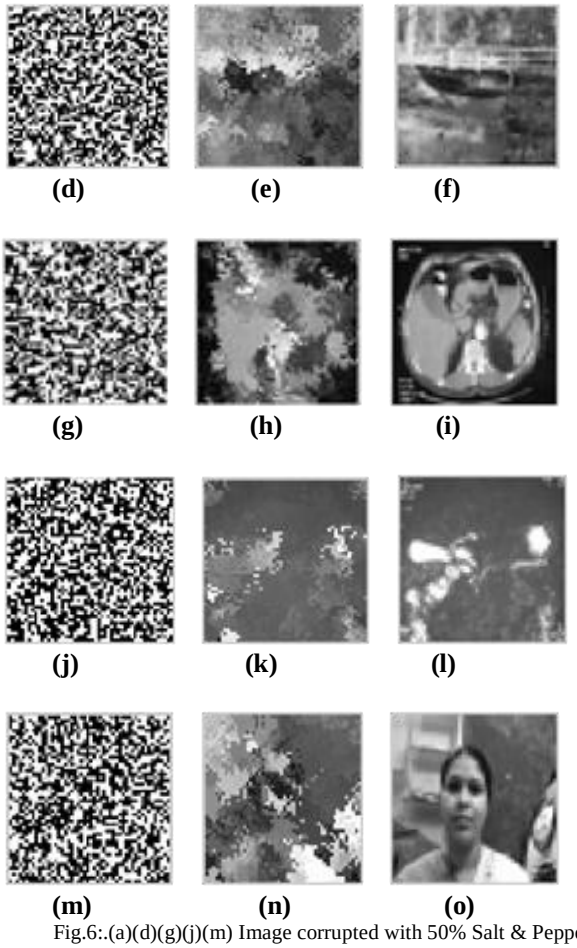


Fig.6:.(a)(d)(g)(j)(m) Image corrupted with 50% Salt & Pepper noise (b)(e)(h)(k)(n) AMF Image (c)(f)(i)(l)(o) Image restored after BFO

TABLE II

COMPARISON OF ADAPTIVE MEDIAN FILTER AND BFO ON THE BASIS OF MSE AND PSNR FOR THE IMAGES, BRIDGE, LENA, SELF CT-SCAN OF PANCREAS AND MR CHOLANGIOPANCREATOGRAM

	Smax for AMF	% of salt & pepper	AMF		BFO	
			MSE	PSNR (dB)	MSE	PSNR (dB)
Lena	5×5	10	60.3376	30.3249	0.0133	66.8832
	9×9	20	125.6840	27.1380	0.0145	66.5087
	13×13	30	213.5816	24.8352	0.0192	65.3087
	17×17	40	295.5836	23.7962	0.0243	64.2740
	21×21	50	429.9872	21.7962	0.0670	59.8726
	25×25	60	528.1380	20.9033	0.1990	55.1414
	29×29	70	783.3608	19.1912	0.2393	54.3388
	33×33	80	1010.8	18.0842	0.2519	54.1182

	43×43	90	2003.7	15.1124	0.3231	53.0372
Bridge	5×5	10	93.9872	28.4001	0.0502	61.1231
	9×9	20	151.0020	26.3410	0.0526	60.9203
	11×11	30	230.2928	24.5080	0.0682	59.7955
	17×17	40	297.5188	23.3957	0.1845	55.4713
	21×21	50	391.1516	22.2074	0.2137	54.8332
	27×27	60	538.8240	20.8163	0.2814	53.6382
	33×33	70	700.4588	19.6770	0.5074	51.0776
	37×37	80	963.8880	18.2905	0.6442	50.0409
	43×43	90	1402.3	16.6623	0.6664	49.8935
CT-Scan of pancreas	5×5	10	165.6924	25.9378	0.1891	55.3634
	9×9	20	227.9096	24.5532	0.2007	55.1049
	17×17	30	324.1800	23.0229	0.2035	55.0447
	21×21	40	424.4564	21.8525	0.2078	54.9535
	27×27	50	682.2984	19.7911	0.2111	54.8855
	31×31	60	840.2984	18.8869	0.2314	54.4864
	35×35	70	1222.7	17.6284	0.2332	54.4535
	39×39	80	1623.9	16.0252	0.3198	53.0815
	43×43	90	3138.2	13.1639	0.6672	49.8882
MRI of pancreas	5×5	10	68.6892	29.7619	0.1779	55.6286
	9×9	20	75.5420	29.3489	0.2169	54.7686
	17×17	30	155.3624	26.2173	0.2198	54.7097
	21×21	40	196.5188	25.1968	0.2204	54.6987
	25×25	50	368.6452	22.4647	0.2316	54.4834
	31×31	60	504.5540	21.1017	0.2382	54.3607
	35×35	70	658.2576	19.9468	0.2446	54.2455
	39×39	80	802.7740	19.0849	0.3046	53.2929
	43×43	90	1528.0	16.2958	0.5781	50.5109
Image of Self	5×5	10	98.6188	28.1912	0.2533	54.0948
	9×9	20	110.3048	27.7049	0.2675	53.8572
	11×11	30	227.3684	24.5635	0.3649	52.5093
	13×13	40	393.2328	22.1843	0.3716	52.4300
	15×15	50	507.0896	21.0800	0.3762	52.3762
	21×21	60	776.4108	19.2299	0.3848	52.2785
	29×29	70	1035.7	17.9785	0.4274	51.8221
	31×31	80	1430.9	16.5747	0.5386	50.8185
	43×43	90	2304.4	14.5052	1.4498	46.5176

Fig.7 shows the convergence plot of the BFO which converges with 2500 iterations. Thus, computation overloading is also low.

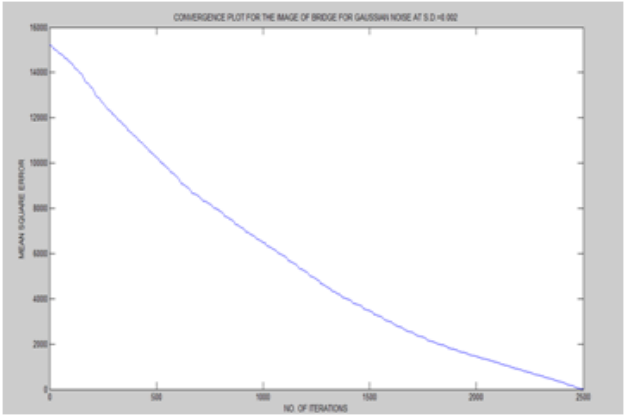


Fig.7: Convergence plot showing reduction of MSE with Number of iterations

V. CONCLUSION

The paper presents an application of BFO as a digital filter to de-noise medical image i.e., CT-Scan and MRI of pancreas. The experimentation in terms of quality matrices like MSE and PSNR show considerable improvement in the quality of restored images. The computational overloading is also low. Thus, this approach of using Soft Computing in conjunction with digital filter will definitely enhance the de-noising capability of digital filters which can find application in sensitive images like medical images.

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