Modification of Bacterial Foraging Optimization Algorithm using Elite Opposition Strategy

Maliki Danlami
Department of Computer Engineering
Federal University of Technology
Minna, Nigeria
danlami.maliki@futminna.edu.ng

Muazu Mohammed Bashir
Department of Computer Engineering
Ahmadu Bello University Zaria
Kaduna, Nigeria
mbmuazu@abu.edu.ng

Olaniyi Olayemi Mikail
Department of Computer Engineering
Federal University of Technology
Minna, Nigeria
mikail.olaniyi@futminna.edu.ng

Jonathan Gana Kolo
Department of Electrical and Electronics Engineering
Federal University of Technology
Minna, Nigeria
jgkolo@futminna.edu.ng

Abstract— **This research work presents the modification of Bacterial Foraging Optimization Algorithm (BFOA) using the elite opposition strategy. The BFOA uses a random search strategy which affect it convergence performance due poor diversification in the search process and the possibility of Oscillatory behaviour towards the search process. The Elite Opposition BFOA is developed to provide more search space so as to enhance more exploitation. The Elite Opposition BFOA (EOBFOA) and the BFOA have been tested using twelve standard benchmark functions (Unimodal and Multimodal benchmark functions). From the simulation result obtained, the EOBFOA outperform BFOA by obtaining better global minimum solution**.

Keywords— **bacterial foraging optimization, elite opposition, benchmark test function, chemotaxis.**

I. Introduction

Optimization is the process of finding the best solution to certain problems base on either finding the maximum or minimum solution with in a certain boundary using a particular objective function. In the world of optimization, traditional optimization methods have been applied in finding the best solution around a specific domain, however the traditional methods (gradient base methods) experience difficulties in finding global optimum [11]. Technically, optimization algorithms can be classified into deterministic and stochastic optimization methods. The deterministic algorithms usually have better solution for a particular optimization problem when the same set of initial values are use at the initial stage of the algorithms. However, such method usually engaged in local search process and easily trapped in local optima. The stochastic optimization methods mostly use a random search process that can enable it escape from local optima and search for a good solution after certain number of iterations [6].

In 2002, Passion was inspired by the foraging behaviour of Escherichia Coli, and propose the Bacteria Foraging Optimization Algorithm (BFOA). The field of BFOA at present has attracted the attention of different researchers' in solving global optimization problem [4]. The BFOA based on social behaviour of the E.Coli bacterial has gain popularity and wider application in solving optimization problem ranging from robot coordination, distributed optimization and control [1]. One of the main challenges of BFOA is its poor convergence capability over multimodal and rough fitness application compared to other evolutionary algorithm such as Genetic Algorithm (GA) and Differential Evolution (DE) [12].

An Adaptive Bacterial Foraging Algorithm (ABFA) was applied in colour image enhancement using fuzzy entropy as an objective function. The ABFA technique optimized the objective function by varying the step size of the bacteria colony. The loss of unnecessary information from the image is reduce by placing constrain during the minimization of the entropy. The ABFA was also compared with the existing image enhancement technique (histogram equalization) and the ABFA outperformed the histogram equalization technique [10]. A multilevel Co-operative Bacterial Foraging Algorithm was applied in colour image segmentation that involved the combination of bacterial chemotaxis, cell-to-cell communication and adaptive scheme for the modification of the Bacterial Foraging Algorithm. A standard test image was used to evaluate the performance of the Co-operative Bacterial Foraging Algorithm with the traditional BFOA. The Co-operative Bacterial Foraging Algorithm outperformed the traditional BFOA in terms of finding a better threshold in less processing time [15].

Bacterial Foraging Optimization Algorithm was modified by varying the population of the bacteria for the purpose of image compression and applying it in fuzzy vector quantization to enable the reduction in average distortion estimation between reconstructed image and training image. The modified BFOA called the BFVPA ensure that the population size of the BFOA scale through variation in the stages of chemotaxis, swarming, elimination and communication sensing in the iteration process. BFVPA perform better than BFOA when compare on PSNR for different images [9]. The same BFVPA was used in the optimization of palm print authentication. Both BFOA and BFVPA were used to select the combination of features that lead to the best performance in palm print base biometric identification system. The accuracy of the authentication system when using BFVPA technique is more than 97.65% when compare with BFOA with 96.65%. [8].

The performance of BFOA was improved using a social behaviour strategy by directing the movement of bacteria towards a lower value of cost function as against the usual random process of the algorithm. The new strategy enhances the lowering of number of iterations of the BFOA when applied to geometric transformation in image registration. The processing time of the algorithm with social behaviour strategy was 24% less when compared with BFOA [13]. Medical image alignment was performed between two images using BFOA. The optimization process was guided by similarity metrics as an objective function which measure the degree of resemblance between the source and target image. The author introduces h-BFOA as a modification to BFOA, due to some unnecessary chemotaxis steps that occurs as a result of oscillation in the position of the bacteria when they are close to the optimal value. The h-BFOA performs higher than the BFOA according to mean square error measure between the two algorithms [3].

The performance of bat algorithm was improved by modifying the algorithm with Elite Opposition Learning (OBL). The standard bat algorithm suffers from poor convergence and also been stuck in local minima. The modified bat base on OBL outperform the standard bat algorithm [17]. An improved BFOA algorithm based on Machine Learning frame work called the IBFO was used in the prediction of severity of somatization disorder. The BFOA was modified using the opposition base learning, the modified algorithm was better in terms of speed and accuracy of good solution [14]. Generally, the efficiency of any new or modified nature inspired optimization algorithm is usually tested using some set of standard benchmark test function which ranges from unimodal and multimodal benchmark test function [5]. The performance of one algorithm cannot be determined by the type of problem it solves most especially if the problems are specific with a different property. Therefore, to evaluate an optimization algorithm one most also identify the kind of problem it performs better [7].

II. Bacterial Foraging Optimization Algorithm (BFOA) Process

The Bacterial Foraging Optimization Algorithms is governed by four processes, which are chemotaxis, swarming, reproduction, elimination and dispersal [16].

A. *Chemotaxis*

Let j , k , and l denote the indices of chemotactic, reproduction and elimination dispersal events. The position of each bacterium in a group of S bacteria at jth chemotactic, kth reproduction steps and the lth elimination- dispersal event be represented in equation 1.

$$P(j,k,l) = \{ \Theta(j,k,l) \; i = 1,2,3 \ldots \ldots .S \tag{1}$$

Θ^i is the position of the ith bacterium, at jth chemotactic step, a kth reproduction step and lth elimination - dispersal event.

Let the cost of the ith bacterium at the location represented as $J(i,j,k,l)$.

The new position of the ith bacteria after a movement (tumbling) is defined as

$$\Theta^i(j+1,k,l) = \Theta^i(j,k,l) + C(i)\Phi(j) \tag{2}$$

Where $C(i)$ indicates the number of steps taken in the random direction indicated by the tumble. If the cost $J(i,j+1,k,l)$ at location $\Theta^i(j+1,k,l)$ is lower than the cost at $\Theta^i(j,k,l)$, then the bacterium will move in the same direction with step size $C(i)$.

B. *Swarming*

In swarming the cell-to-cell communication is performed via information exchange through attractant to swarm to together or via repellent to isolate each other. The cell to cell communication signal by the ith bacterium is represented in equation (3).

$$\sum_{i=1}^{S} J_{cc}\left(\theta, \Theta^i(j,k,l)\right), i = 1,2,3 \ldots \ldots \ldots .S \tag{3}$$

Collectively such cell-to-cell attraction and repulsion is given by equation (4).

$$J_{cc}\left(\theta, \Theta^i(j,k,l)\right) = \sum_{i=1}^{S} J_{cc}\left(\theta, \Theta^i(j,k,l)\right) = a + b \tag{4}$$

$$a = \sum_{i=1}^{S}[-d_{attract}\exp(-w_{attract}\sum_{m=1}^{p}(\Theta_m - \Theta_m^i)^2)] \tag{5}$$

$$b = \sum_{i=1}^{S}[-h_{atrepellent}\exp(-w_{repell}\sum_{m=1}^{p}(\Theta_m - \Theta_m^i)^2)] \tag{6}$$

$d_{attract}$ =depth of attractant

$w_{attract}$ = width of attractant

$h_{repellent}$ =height of repellent

$w_{repellent}$ = weight of repellent

Where,

$J_{cc}(\Theta, P(j,k,l))$ is the objective function value. in swarming, the individuals climb as in equation (7)

$$J(i,j,k,l) = J(i,j,k,l) + J_{cc}(\Theta,P) \tag{7}$$

C. Reproduction

The reproduction of next generation bacteria cells occurs after certain number of chemotactic steps say Nc. Let the number of reproductive steps be Nre, the bacterium health is measured as the sum of its fitness value throughout its life

$$health = \sum_{j=i}^{Nc} J(i, j, k, l) \tag{8}$$

D. Elimination Dispersal

This event is also predefined as the number of (Ned) of elimination dispersal event of a bacterium. The (Ped) is the probability of elimination-dispersal event of a bacterium. The chemotaxis provides the basis for local search. In case of avoiding a halt in local optima, bacteria will tend to disperse to other location in the search space with respect to the probability (Ped).

III. MODIFICATION OF BFOA USING ELITE OPPOSITION STRATEGY

The opposition-based strategy is basically a computational intelligence strategy that considers the current individual and its opposite individual simultaneously in order to get a better approximation. The elite opposition base strategy, which is an extension of opposition base strategy is one of the effective approaches in enhancing the performance of Evolutionary Algorithms (EA). Let $Pe[x, y]$ be a real number. The opposition number of $P(P^*)$ is defined in equation (9)

$$P^* = x + y - P \tag{9}$$

The main idea of elite based opposition is for any visible solution, calculate and evaluate the opposite solution at the same time, and chose the best individual. The equation for the elite base opposition is given in equation 10.

$$P1 = k\left(d_{ai} + d_{bi}\right) \tag{10}$$

$$x^*_{i,j} = P1 - x_{i,j} \tag{11}$$

Where i=1, 2, ……,N; , j= 1,2,……n and k is a random variable [2]. Where N is the population size, and $(d_{ai}\ d_{bi})$ is the dynamic bound of decision variable which can be obtained as follows:

$$d_{ai} = \min(x_{i,j}) \tag{12}$$

$$d_{bi} = \max(x_{i,j}) \tag{13}$$

The flowchart for the EOBFOA is shown in Fig. 1

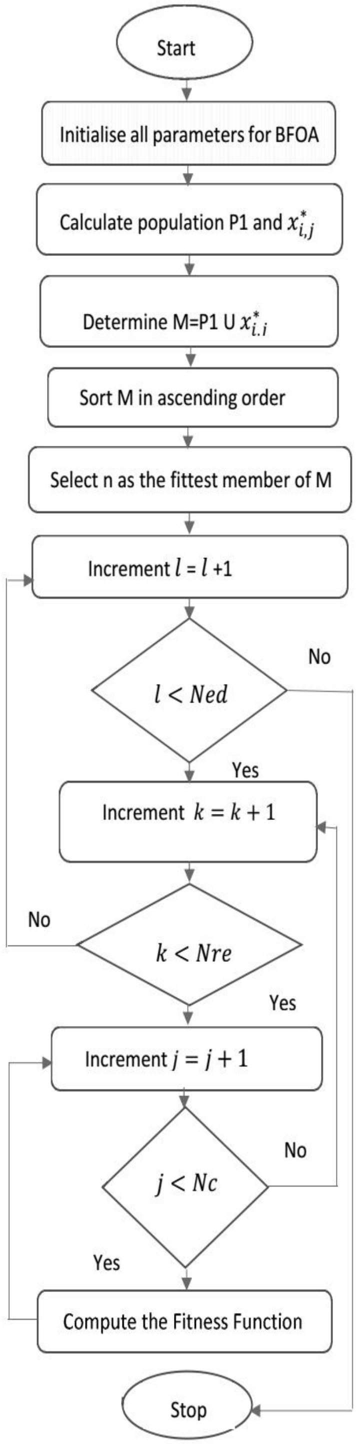

Fig. 1. Flowchart of Elite Opposition BFOA

III. PERFORMANCE EVALUATION OF BFOA AND EOBFOA

The performance of both algorithms was evaluated using twelve standard benchmark functions. The range of each test function and the Global Minimum (GM) are shown in table 1. The EOBFOA from analysis, performs better in all the test function compare to BFOA on both unimodal ($f1$, $f2$, $f3$, $f4$, $f5$, $f6$) and ($f7$, $f8$, $f9$, $f10$, $f11$, $f12$) benchmark test function.

TABLE 1: BENCHMARK FUNCTIONS FOR BFOA AND EOBFOA

Function	Equations	Range	GM
$f1$ (Griewank)	$f_1(x) = \frac{1}{4000}\sum_{i=1}^{n}(x_i^2) - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	[-600 600]	$f(X^*) = 0$
$f2$ (Sphere)	$f_2(x) = \sum_{i=1}^{n} x^2$	[-5.12 5.12]	$f(X^*) = 0$
$f3$ (Zakrov)	$f_3(x) = \sum_{i=1}^{n} x_i^2 + (\frac{1}{2}\sum_{i=1}^{n} (x_i)^2 + (\frac{1}{2}\sum_{i=1}^{n} (x_i)^4$	[-5 10]	$f(X^*) = 0$
$f4$ (Schwefel's 221)	$f_4(x) = f(x_1, \dots, x_n) = max_{i=1,\dots,n}\lvert x_i \rvert$	[-100 100]	$f(X^*) = 0$
$f5$ (Schwefel's 222)	$f_5 = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	[-100 100]	$f(X^*) = 0$
$f6$ (Schwefel's 223)	$f_6(x) = f(x_1, \dots, x_n) = \sum_{i=1}^{n} x_i^{10}$	[-10 10]	$f(X^*) = 0$
$f7$ (Ackley)	$f_7(x) = -aexp\left(\sqrt{\frac{1}{d}\sum_{i=0}^{d} x_i^2}\right) - \exp(\frac{1}{d}\sum_{i=1}^{d} cos(cx_i)) + a +$	[-32.7 32.7]	$f(X^*) = 0$
$f8$ (Drop wave)	$f_8(x) = -\frac{1 + \cos(\sqrt{\sum_{i=1}^{n} x^2})}{\left(\frac{1}{2}\right)\left(\sum_{i=1}^{n} x^2\ i\right) + 2}$	[--5.2 5.2]	$f(X^*) = -1$
$f9$ (Goldstein and price)	$f_9 = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1$	[-2 2]	$f(X^*) = 3$
$f10$ (Salomon)	$f_{10} = -\cos\left(2\pi\sqrt{\sum_{i=1}^{D} x_i^2}\right) + 0.1\sqrt{\sum_{i=1}^{D} x_i^2} + 1$	[-100 100]	$f(X^*) = 0$
$f11$ (Rosenbrok)	$f_{11}(x) = \sum_{i=1}^{n-1}[(x_i - 1)^2 + 100(x_i^2 - x_{i+1})^2]$	[-5 10]	$f(X^*) = 0$
$f12$ (Rastrigin)	$f_{12} = \sum_{i=1}^{n}[x_i^2 - 10\,cos(2\pi x_i - x_{i+1})^2 + 10]$	[-5.12 5.12]	$f(X^*) = 0$

A Unimodal Test Function

Most of the Unimodal Test function are continuous, convex and the function can be defined over n-dimensional space. Table 2 shows the results for unimodal test function base on statistical analysis. Fig. 2 to Fig. 6 shows the converging plot of BFOA and EOBFOA on different unimodal test function.

TABLE 2: UNIMODAL BENCHMARK FUNCTIONS

Algorithm	Metrics	$f1$	$f2$	$f3$	$f4$	$f5$	$f6$
BFOA	Best	5.7632E-05	8.8350E-05	3.0103E-04	0.0070	0.0101	2.5889E-19
	Worst	6.9968E-05	2.1180E-04	5.8613E-04	0.0298	0.0142	7.6261E-19
	Mean	6.3800E-05	1.5007E-04	4.4358E-04	0.0184	0.0122	3.8132E-19
	Std.	8.7227E-05	8.7292E-05	2.0159E-05	0.0161	0.0029	5.3923E-19
EOBFOA	Best	9.7350E-07	1.9324E-05	6.2877E-05	0.0081	0.0048	2.2573E-27
	Worst	5.2340E-05	2.2478E-04	1.7433E-04	0.0090	0.0049	1.0605E-23
	Mean	2.6657E-05	1.2205E-04	9.0307E-05	0.0086	0.0048	5.3036E-24
	Std.	3.6322E-05	1.4528E-04	1.1882E-04	6.1947E-04	7.4972E-04	7.4972E-24

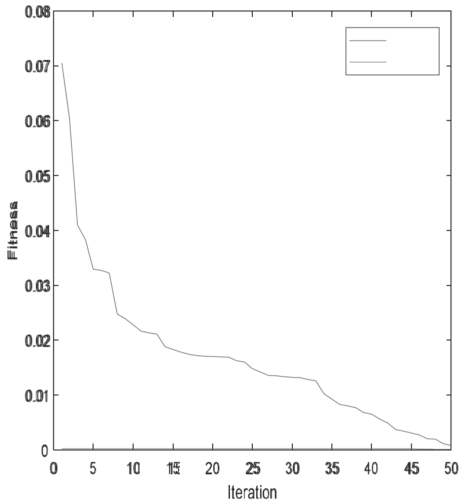

Fig. 2. Griewank BFOA and EOBFOA

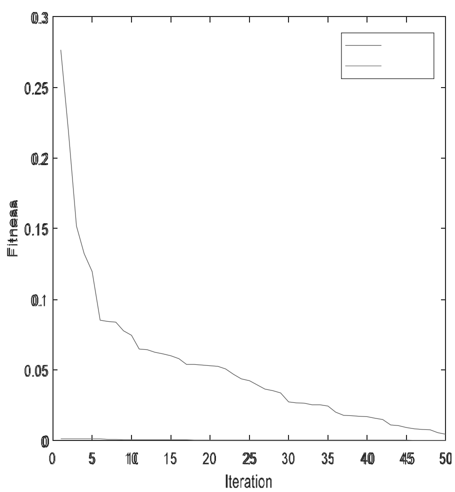

Fig. 2. Sphere BFOA and EOBFOA

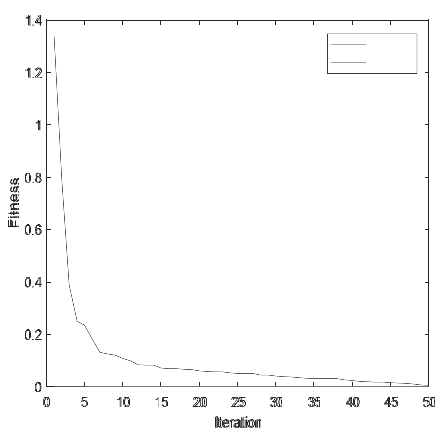

Fig. 3. Zakrov BFOA and EOBFOA

B. Multimodal Test Functions

The optimization test using multimodal benchmark functions was to check for the exploration performance of

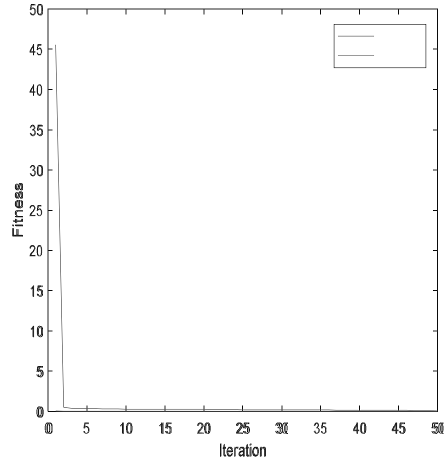

Fig. 4. Schwefel's 221 BFOA and EOBFOA

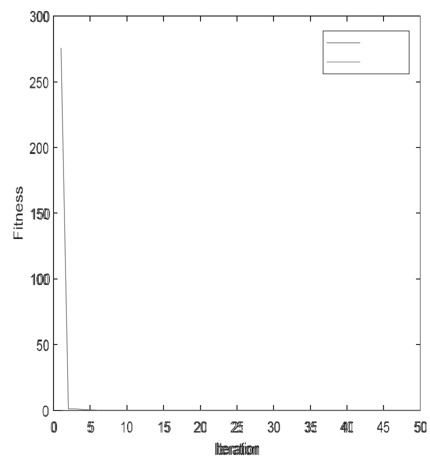

Fig. 5. Schwefel's 222 BFOA and EOBFOA

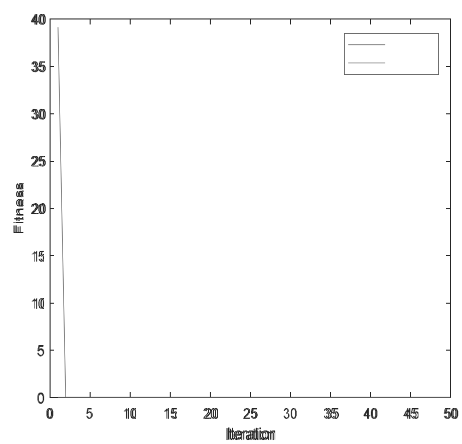

Fig. 6. Schwefel's 223 BFOA and EOBFOA

the BFOA and EOBFOA. Table 3, shows the simulation results for the using the multimodal test function and the graphical representation of the convergence plot is also shown in Fig. 7 to Fig. 12.

TABLE 3: MULTIMODAL BENCHMARK FUNCTIONS

Algorithm	Metrics	$f7$	$f8$	$f9$	$f10$	$f11$	$f12$
BFOA	Best	0.0412	-0.9612	3.2677	8.6822E-04	0.1105	0.0872
	Worst	0.1968	-0.9638	3.2752	0.0053	0.1223	0.1093
	Mean	0.1190	-0.9747	3.2715	0.0032	0.1164	0.0983
	Std.	0.1100	0.0153	0.0053	0.0032	0.0084	0.01560
EOBFOA	Best	0.0146	-0.9923	3.0262	2.9487E-04	0.0013	0.0070
	Worst	0.0425	-0.9886	3.1375	0.0036	0.0124	0.0108
	Mean	0.0285	-0.9904	3.0819	0.0020	0.0068	0.0089
	Std.	0.0198	0.0026	0.0787	0.0024	0.0078	0.0027

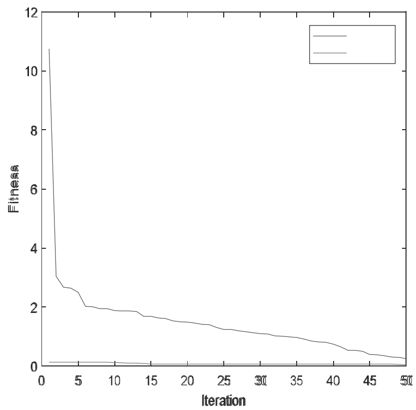

Fig. 7. Ackley BFOA and EOBFOA

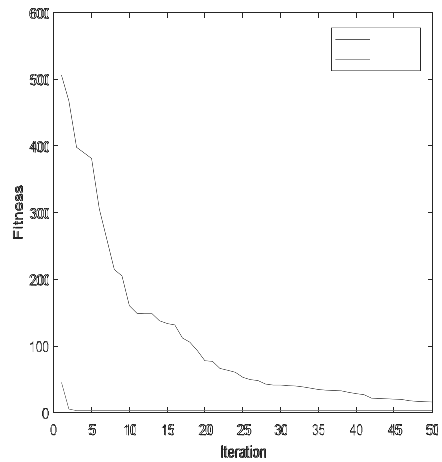

Fig. 9. Goldstein price BFOA and EOBFOA

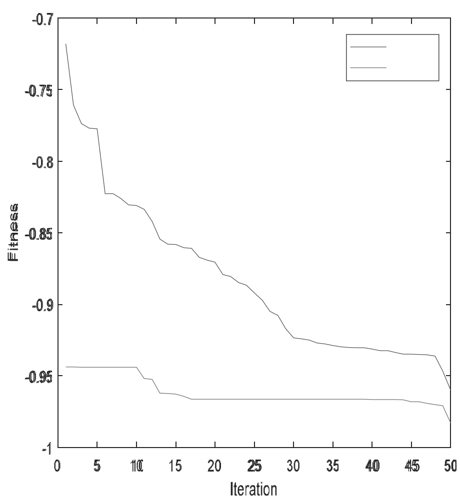

Fig. 8. Drop wave BFOA and EOBFOA

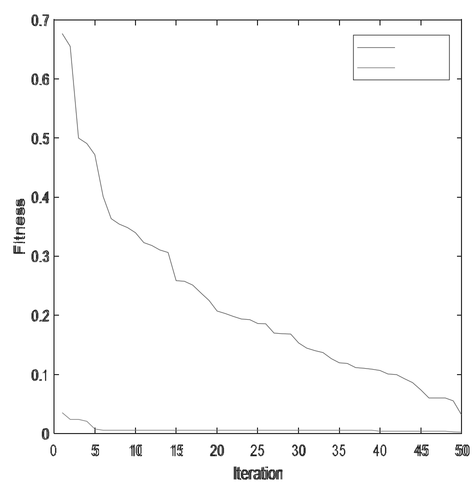

Fig. 10. Salomon BFOA and EOBFOA

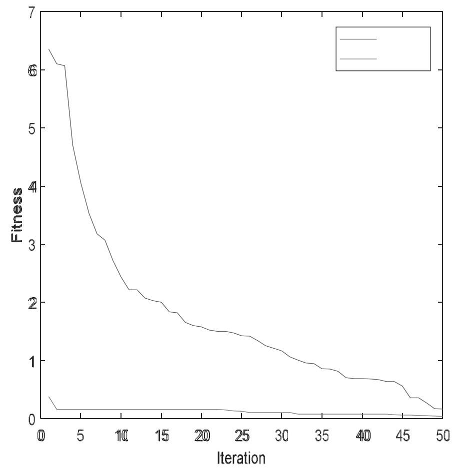

Fig. 11. Rosenbrok BFOA and EOBFOA

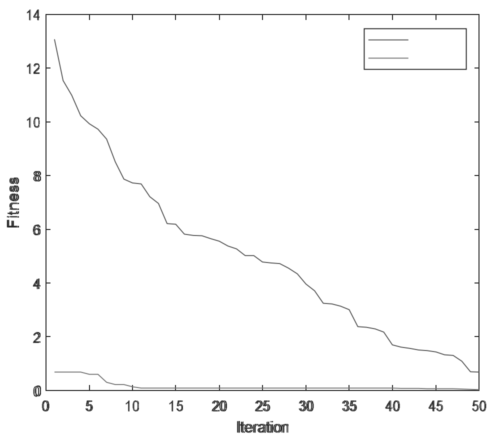

Fig. 12. Rastrigin BFOA and EOBFOA

IV. CONCLUSION

In this research, the EOBFOA is developed by modifying BFOA using the elite opposition strategy and tested on both unimodal and multimodal benchmark test function. The evaluation of both algorithms using best, worst, mean and standard deviation is performed, with the EOBFOA converging to a better solution than the BFOA. The convergence plot further shows that the elite opposition strategy provides more improvement to the standard BFOA by enhancing more diversification of the algorithm during search process. Further research will base on evaluating the performance of the EOBFOA at different parameter settings and also its application to medical images.

REFERENCES

[1] S. Amrinder, and Sonika, J. *A Systematic Way for Image Segmentation Based on Bacterial Foraging Optimization Techniques*. International Journal of Computer Science and Information Technologies. 2014.Vol. 5. Pp 130-133.

[2] Q. Chiwen, Z. Shi'an, F Yanming, and Wei, H. *Chicken Swarm Optimization Based on Elite Opposition-Based Learning*. Hindawi Journal of Mathematical Problems in Engineering. 2017. Pp 1-20.

[3] B. Enrique, V. Andrea, D. Sergio, and C. Oscar, *Bacterial Foraging Optimization for Intensity-Based Medical Image Registration*. 2015 IEEE Congress on Evolutionary Computation (CEC). 2015. Pp 2436-2443.

[4] L. Jun, D. Jianwu, B. Feng, and W. Jiansheng, *Analysis and Improvement of the Bacterial Foraging Optimization Algorithm*. Journal of Computing Science and Engineering. 2014. Vol. 8, No. 1. Pp 1-10.

[5] H. Kashif, N. Mohd., S. Mohd., C. Shi., and N. Rashid. *Common Bench Mark Functions for Metaheuristics Evaluation: A Review.* International Journal of Informatics Visualization. 2017. Pp 218-222.

[6] Z. Lina, L. Ligiang., Y. Xin-She, and D. Yuntao. *A Novel Hybrid Firefly Algorithm for Global Optimization*. https://doi.org/10.1371/journal.pone.0163230. 2016 Pp 1-17.

[7] J. Momin,. and Y. Xin-She, *A literature Survey of Bench Mark Functions for Global Optimization Problems. International.* Journal of mathematical Modelling and Numerical Optimization. 2013.Vol. 4. No. 2, Pp 150-194.

[8] S. Nandita, C. Amitava, and M. Sugata. *BFOA with Varying Population Based Feature Selection and Optimization Based Feature Selection and Optimization in Palm Print Authentication- A Comparative Study*. 2017 IEEE Calcutta Conference. Pp 236-240.

[9] S. Nandita, C. Amitava, and M. Sugata. *Fuzzy VQ Based Image Compression by Bacterial Foraging Optimization Algorithm with Varying Population*. 2014 International Conference on Control, instrumentation, energy & Communication (CIEC). Pp 641-645.

[10] P.V. Om, R. C. Rishi, and Abhinav, G. *An Adaptive Bacterial Foraging Algorithm for Color Image Enhancement*. Annual Conference on Information Science and System (CIES). 2016. Pp 1-6.

[11] H. A. Rahib, and T Mustafa.. *Experimental Study of Specific Bench Mark Function for Modified Monkey Algorithm*. 12th International Conference on Application of Fuzzy System and Computing, ICAFS 2016. Pp 595-602.

[12] A. Sasithradri,, and N.N. Singh. *Synergy of Adaptative Bacterial Foraging Algorithm and Particle Swarm Optimization Algorithm for Image Segmentation.* 2014. International Conference on Circuit, Power and Computing Technologies [ICCPCT]. Pp 1503-1506.

[13] B. Siviu-Ioan, R. Florin, L. Ramona, Cristina, D. N. and C Hariton,. *Social Behaviour in Bacterial Foraging Optimization Algorithm for Image Registration*. International Conference on System Theory Control and Computing. 2014. Pp 330-334.

[14] L.V. Xinen., C. Huiling,. Z. Qian, I. Xujie, H. Hui., and W. Gang. *An Improved Bacterial Foraging Optimization Algorithm Based Machine Learning Framework for Predicting the Severity of Somatization Disorder*. https://www.mdpi.com/1999-4893/11/2/17. 2018. Pp 1-18.

[15] L. Yang. H. Kunyuan,, Z. Yunlong, and Hanning, C. Color Image *Segmentation Using Multi Thresholding-Cooperative Bacterial Foraging Algorithm*. The 5th Annual IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems. 2015. Pp 181-185.

[16] T.A. Yasmina,., and F. Hadria, *A Hybrid Bacterial Foraging Optimization Algorithm and a Radial Basic Function Network for Image Classification.* Journal of Information Processing Systems. 2017.Vol. 13, No. 2. Pp 215-235.

[17] H. Zaharudeen, M.B, Muazu, K.A Abibulah, and T.A Salawudeen. *Development of a Modified Bat Algorithm Using Elite Opposition-Based Learning*. 2017 IEEE 3rd International Conference on Electro-Tecnology for National Development (NIGERCON). Pp 144-151