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A Survey on Fruit Fly Optimization Algorithm and Its Improvements.

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ABSTRACT

This paper presents a survey on Fruit Fly Optimization Algorithm (FOA) and its variance. It is one of the most used swarm optimization algorithms in recent years. Its significant features are investigated in this paper with its applications. When using FOA as a metaheuristic algorithm, its convergence to optimality and it has the effective searching capabilities comparatively. Hence, FOA can be deployed in many applications, especially in the Support vector machine, travelling salesman problem, PID controller tuning and so on. This paper focuses on a broad survey on FOA and Improved FOA (IFOA) algorithms, its performance measures and discussed along with their applications. This survey concludes that the FOA can be hybridized with other machine learning algorithms to achieve higher accuracy.

Keywords: Fruit fly optimization algorithm, metaheuristic, optimization, improved FOA, Iterative algorithm.

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INTRODUCTION

The Particle Swarm Optimization (PSO) is considered as one among the Stochastic Optimization methods based on population. In 1995, this technique can be introduced by Dr. Kennedy and Dr. Eberhart established under the inspiration of the general behavior of bird flocking or fish schooling. This technique is compared with many algorithms like Genetic Algorithm, etc. The main advantage of this technique is to implement in an easy manner. There are some parameters needs some adjustment. This PSO technique was practically applied in many areas like training the artificial neural network, controlling fuzzy system, function optimization and for some other GA based areas. For high-dimensional space, the local optimum is easy to fall and for iterative process low convergence rate is to be occurred are considered as a disadvantage of PSO. Recently The Fruit Fly Optimization (FOA) has been introduced the Swarm Intelligence as a new method. This method is used under the foraging behaviors of fruit flies which appears as the competitiveness among conventional evolutionary algorithms like this PSO (Particle Swarm Optimization) algorithms.

In accordance with different application types which are specified beyond in Table 1, the FOA considered as the outstanding optimization algorithm.

Table 1: Various usage areas of FOA

Author	Year	Problems using FOA	Usage Areas
Pan	2012	An Optimization problem	Financial distress model
Li et al	2013	Problem during Forecasting	Power load in electric power industry
Lin	2013	To optimize the artificial neural network for analyzing the service satisfactory. s	Web auction logistics service
Bao and Sheng	2013	For Searching optimal parameter values	Fuzzy-PID controller using Fractional order
Tu et al	2012	To optimize generalized regression neural networks	Observing the performance of the business
Li et al	2012	Optimizing the two parameters for the least squares SVM	Forecasting the electricity for annual consumption in China
Chen et al	2013	To perform the satisfaction analysis by optimizing the grey neural network model	E-Business service.

In 2011, PAN suggested this FOA. For the past recent years, Researchers and Scholars are suggested to use so many metaheuristic algorithms for solving the occurrence of optimization problems and it must use when the solution of the problem is difficult. Many of these metaheuristic algorithms are intelligent and stochastic and they can be suggested by inspiring animal behaviors. In the way of perception and sensing, fruit fly can be greater than another flying species. Every fruit flies using their vision organs and smelter capacity for reaching the food. At first, it uses its osphresis organs to find all types of scents via air and then it will fly according to that food location. By using its vision organs, it gets closer to the food. FOA is one among the metaheuristic algorithms and their foraging behaviors are developed by inspiring to easily reach the global optimum. It has some advantages are as follows:

- It is simply structured.
- Solving the problem in fast manner.
- It is easily adaptable for applications.
- Easily understandable and least number of lines of coding.
- It is a stabled algorithm.
- Few parameters are used.

Where in some cases, the researchers found some of the deficiencies while using this FOA and they mentioned as a disadvantage in various literatures. The following are the disadvantages of using FOA in various applications are listed.

- Swarm's First food location are to be poor.
- Blindness occurs during solution updating.
- Optimization problems only used this.
- Strategic updating is small and it is fixed.
- It easily traps into the local optimum.
- It always gives a positive value for the fitness function.

To overcome these deficiencies the authors stated some of the strategies like, by improving the algorithm for a better result etc.

In recent years, Fruit Fly Optimization algorithm was proposed, but its theory is not in mature stage, the research area of this algorithm still in the starting stage. The advantages and disadvantages of this algorithm are considered by many scholars. They have organized some series of improvemental studies [1] under domestic and in foreign: In Literature [2] quadratic optimization is to be achieved and to occur the high value parameters by integrating the logistic mapping over global searching technique. In Literature [3] Proposing a new FOA under bacterial chemotaxis behavior by introducing the conversion operation of repulsion and attraction. In Literature [4] by mutated the Gaussian, in order to achieve the quadratic optimization, adaptive mutated fruit fly optimization algorithms proposed and used for copying the best individuals during its operation. In Literature [5] to optimize the evolutionary mechanisms of FOA by integrating with chaotic algorithm and it forward over adaptive chaotic fruit fly optimization algorithms. To get the excellent achievement in engineering designs there are some other scholars applying this FOA.

The remaining sections in this survey paper are described as follows; in Section 2, detailed description about the FOA, where the Section 3 includes the usage of the FOA in Support Vector Machine. In Section 4, improving the algorithm (IFOA) and uses in Travelling Salesman Problem are discussed. The experimental analysis is discussed in section 5. In section 6, some of the FOA applications are mentioned. Finally, in section 6, this paper concludes with some results.

FRUIT FLY OPTIMIZATION ALGORITHM

A Fruit Fly Optimization (FOA) technique which is successful and logically addressing the parameter set. According to the basic foraging Drosophila's behavior, this Fruit Fly Optimization Algorithm was expanded. Visually sensing capacity and the olfactory capabilities are superior to other species than a fruit fly to locate their food with its instinct. Iterative process helps to make use of a food searching capability of a fruit fly and finding the distance and the direction to reach the location of a food. Likewise the next iteration is based on the previous information to calculate the high accuracy and to reduce the computational time. Where the classification in accuracy, sensitivity, specificity and also AUC can be examined for effectiveness and efficiency of the data sets in the medical field which has been taken from the UCI i.e., the machine learning repository which is to be occurred in this proposed system.

The FOA steps are demonstrated in Figure 1 and it is described by the following algorithm [6].

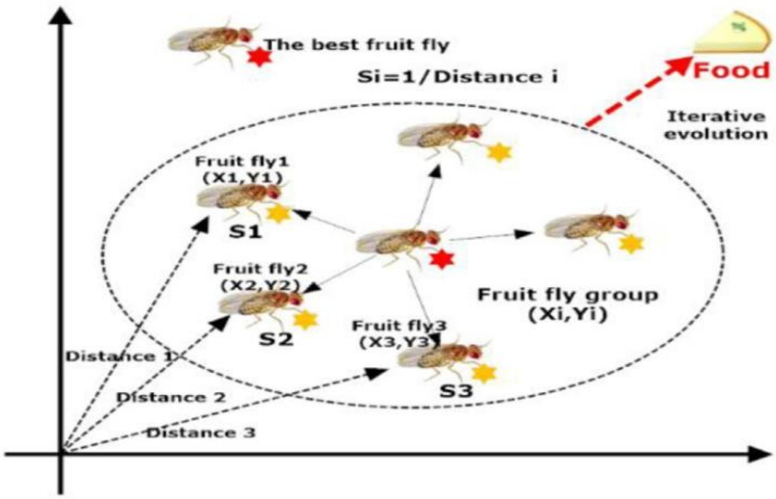


Figure 1: Fruit Flies Food Searching in Various Iteration [6]

Step 1: Parameter Initialization.

FOA parameters are initialized like the maximum no. of iteration, the size of the population, fruit fly's initial swarming location spot (X_axis, Y_axis) and their air travel distance at random manner.

X_axis = Rands (1,2)
Y_axis = Rands (1,2)

Step 2: Initializing Population.

For population, j represent to provide the randomly chosen location (Xj, Yj) with the food searching distance for each and every fruit fly.

X_j = X_axis + RandomValue
Y_j = Y_axis + RandomValue

Step 3: Population Evaluation.

Origin (Dst) can be calculated and compute the judgement value (Sml) of the smell concentration which is the food location's reciprocal distance towards the origin.

$$Dst_i = \sqrt{(X_i^2 + Y_i^2)}$$
$$Sml_i = 1/Dst_i$$

Step 4: Replacement.

Judgement value (Sml) which represents the smell concentration, is replaced with the judgement function for smell concentration and then to find the individual location for smell concentration of a fruit fly ($Smell_i$).

$$Smell_i = Function\ (Sml_i)$$

Step 5: Finding the maximal smell concentration.

Maximum concentration of smell and then the corresponding fruit fly's location can be determined.

[bstSmlbstIndx] = max (Sml)

Step 6: Maintaining the maximum of smell concentration.

Coordinating the x value and the y value in retaining a maximum smell concentration value, by using these values the fruit fly can fly in the direction of the location.

Smlbst = bstSml
X_axis = X (bstIndx)
Y_axis = Y (bstIndx)

Step 7: Optimization with Iterative Process.

Repeating the steps from 2-5 by entering its iterative optimization. If there is no longer superior for smell concentration compared to the previous iteration and then the circulation stops (while reaching the maximal iterative number).

The following flowchart (figure 2) represents the Classical method of FOA [7].

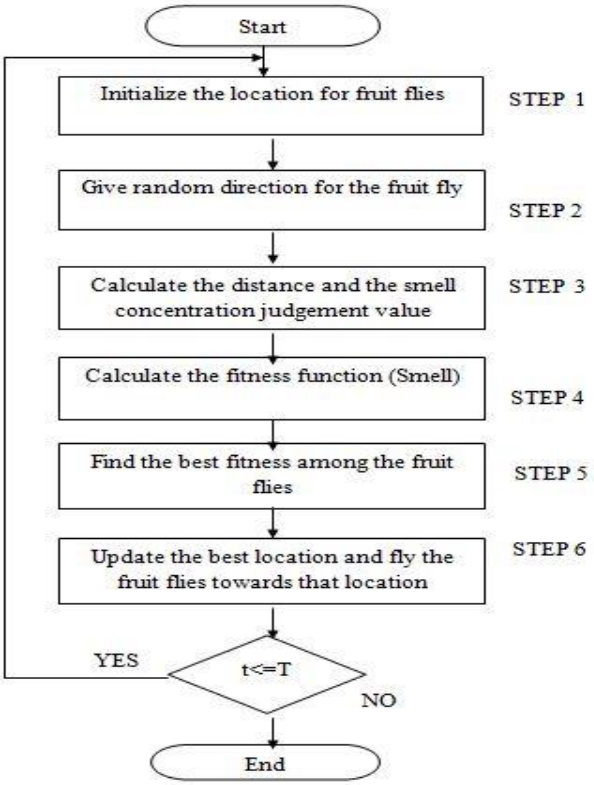


Figure 2: Flowchart of Classical FOA [7]

FOA FOR SUPPORT VECTOR MACHINE

The FOA-SVM is evaluated for the effectiveness and efficiency of well-known datasets. Obtaining more appropriate model parameters by using FOA-SVM which significantly reducing the computational time for generating high classification accuracy. There are two procedures primarily comprised in this FOA-SVM method: the inner and outer parameters optimization and classification performance evaluation. SVM parameters are dynamically adjusted the 5-fold CV analysis, which is nothing but a cross validation analysis during the inner optimization parameter processing. Then, to perform 10-fold CV analysis the prediction model for SVM, the classification in the outer loop is to be performed by obtaining the optimal parameter. Finally via the 5-fold CV the average for the test accuracy is aided by using the SVM classifier.

For adjusting the parameter, the following steps are processed [6].

Pseudo code representation of parameter Algorithm

Begin
For *j=1 to sizepop*
Begin
For *j=1 to sizepop*

After initializing the distance reciprocal S (j, 1) and S (j, 2) then Setting the parameters for SVM; Calculating the value of initial fitness;

SVM is a model which is to be trained along with its reciprocal distance and the smell arrays test results are recorded;
End
[bstSml, bstindx] = max (Smell);
pp = cp;
bstCV = bstSml;
bstC = S (bstIndx, 1);
bstg = (bstIndx, 2);
For *j = 1: maxigen*
For *k=1 to sizepop*
*X (k, :) = X_axis + ax*rand () – bx;*
*Y (k, :) = Y_axis + ax*rand () – bx;*
$Dst_{(k,1)} = (X_{(k,1)}^2 + Y_{(k,1)}^2)^{1/2}$;
$Dst_{(k,2)} = (X_{(k,2)}^2 + Y_{(k,2)}^2)^{1/2}$;
Sml (k, 1) = 1/Dst (k, 1);
Sml (k, 2) = 1/Dst (k, 2);
Setting the parameters for SVM with Sml (k, 1) and Sml (k, 2);
Calculating the value of initial fitness;

SVM is a model which is to be trained along with its reciprocal distance and the smell arrays test results are recorded;
End
[bstSml, bstIndx] = max (Smell);
If *(bstSml > bstCV)*
pp=cp;
bstC = S (bstIndx, 1);
bstg = S (bstIndx, 2);
bstCV = bstSml;
End If
End
Return bstC, bstg;
End

The method FOA-SVM [6] based on, the population no. (p), the problem scales (D), the no. of training samples (L), and the no. of generations (g) for computational complexity. Then the on the whole computational complexity is, **O (SVM, FOA) = O (Initialize) + g* (O (SVM) + O (FOA updated position) + O (FOA's calculation for the global best value) + O (Final Output))**.

PERFORMANCE EVALUATION MEASURE

It can be evaluated under the accuracy in classification (ACC), the area which depends on the operating characteristic curve for the receiver (AUC) based criteria, then specificity and sensitivity performance in the proposed model. The formulas using to calculate these criteria are followed [6]:

ACCURACY = TP + TN/ (TP + FP+ FN+ TN) * 100 %
SENSITIVITY = TP/ (TP + FN) * 100 %
SPECIFICITY = TN/ (FP + TN) * 100 %

In general, TP refers to no. of true positives, FN refers to no. of false -ve, TN refers the no. of true -ve, FP refers the no. of false +ve.

In two-class problems the classifiers are compared to find the best methods for AUC belongs to the ROC curve.

The most suitable method is analyzed as a FOA-SVM. For classification problems it requires only a moderate computational cost of producing its excellent performance and it has the capability to acquire more

proper settings for parameters and for SVM classifier it has the higher generalization capability over a diagnostic problem. The unique olfactory and visual sense of the FOA is its advantageous performance. Various evaluation metrics are performed as a valuable alternative FOA-SVM method can be utilized.

IFOA FOR TRAVELING SALESMAN PROBLEM

For several optimization problems the FOA gives good performance by improving some factors in the algorithm. So the Traveling Salesman Problem (TSP) tries to apply this algorithm. There is a slight modification in several aspects the FOA is modified only because of this Traveling Salesman Problems characteristics named as Improved Fruit Fly Optimization Algorithm (IFOA). This new IFOA slightly differs from the original FOA by including the GA and PSO algorithms. In this IFOA the reciprocal of distance as smell concentration, but take hold of the essence of the FOA and its decision value is not used when compared to the FOA. The disperse phase of searching population randomly as like as the stage of fruit flies food searching smell then the phase of visual search is compared to the time for gathering the population of fruit flies to the best location. According to the swarm and experience of the individual, the own position of the fruit flies is adjusted constantly during the search process. Continuously processing like this, the search space of the solution is to be expanded, and its prematurity of convergence is to be prevented. Then the speed of the convergence of this algorithm is also improved. For analyzing the optimization mechanism of the original FOA by using the search model of the solution. From this it shows that the IFOA is not only for solving the function of extreme value problem, it is a common model for optimization problem.

The working steps of the Improved FOA as follows:

- Initializing the Population
- To record the extreme value of individual and global by calculating the fitness
- To generate the new particles, cross with individual and global extreme and through the process of smell and visual search we get the new solution.
- Calculate the fitness value and update the current and the previous optimal value.
- By crossover and mutation the population generates new particles based on the last optimal value and through the process of smell and visual search we get new solutions.
- Again calculate the fitness and then record the optimal value with the condition of judging whether the stopping criteria reach or not.
- If the stopping criteria are reached, then the population initializations are occurring or if not reaching the stopping criteria, then again process the steps of calculating the fitness and so on.

Pseudo code representation of improved Fruit Fly Optimization Algorithm

---

Parameter : *nMax, sizepop, maxgen*
Output : *optimal solution yy*

```
1.  Load the city coordinates, to calculate the distance between cities
2.  Initialization
Set mMax, sizepop, maxgen and particle initial location
FOR j=1 to sizepop
    Individual (j, :)=randpperm (m)
END FOR
3.  Get the extreme value of individual and global (Pbest and Gbest)
FOR j=1: size (x, 1)
    For k=1: size (ctycoor, 1) -1
            indFit (j)=indFit (j)+ctyDist (x (j, k), x (j, k+1)
    END FOR
            indFit (j)=indFit (j)+ctyDist (x (j, k), x(j, 1), x(j, size (ctycoor, 1))
END FOR
4.  Generate new particles by crossover
    co1=unirnd (m-1)
    co2=unirnd (m-1)
WHILE co1==co2
```

```
        co1=rnd (rand* (m-2)) +1
        co2=rnd (rand* (m-2)) +1
END WHILE
        cb1=min (co1, co2)
        cb2=max (co1, co2)
    5.  Generate new particles by mutation
        co1=rnd (rand* (m-1)) +1
        co2=rnd (rand* (m-1)) +1
WHILE co1=co2
        co1=rnd (rand* (m-2)) +1
        co2=rnd (rand* (m-2)) +1
END WHILE
        tmp=xnw1 (j, co1)
        xnw1 (j, co1) =xnw1 (j, co2)
        xnw1 (j, co2) =tmp
    6.  FOR j=1:sizepop
                IF indFit (j) <rcdPbest (j)
                        rcdPbst (j) =indFit (j)
                END IF
        END FOR
    7.  FOR k=1: m-1
                dst=dst+ctyDist (xnew1 (j, k), xnw1 (j,  k+1)
        END FOR
IF indFit (j) >dst
        Indi (j, :)=xnw1 (j, :)
END IF
    8.  Output yy
```

To improve some specific factors of the FOA, by adjusting some of the parameters was tested by using the above given algorithm named as a Improved FOA which is assured by some researchers.

EXPERIMENTAL ANALYSIS

In this section, the experimental analysis is to be discussed for both FOA and IFOA. By using MATLAB 7.0 the coding of the both algorithms can run with the help of the PC along with 2.53GHz by having the memory up to 2G. Here the number of initial population is given as 20 and 30 populations and the no. of iterations 200,300,500 and 1000 are used for k value. The following Figure 3 shows the flying routes for the fruit flies [8] and then, the Figure 4 and Figure 5 shows the best fitness values [8] for both the algorithms respectively belongs to the optimization process.

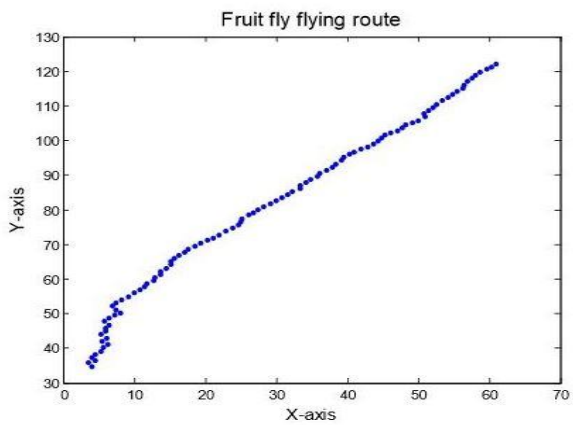
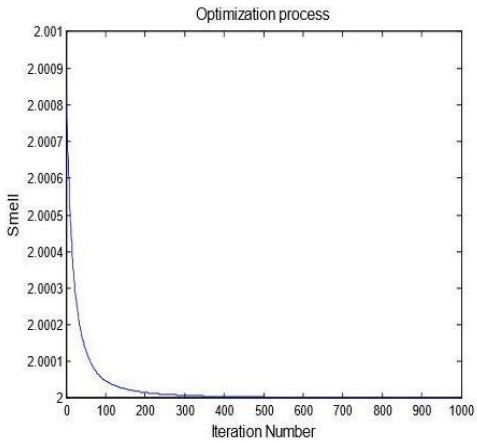


Figure 3: Flying route for the fruit flies [8]



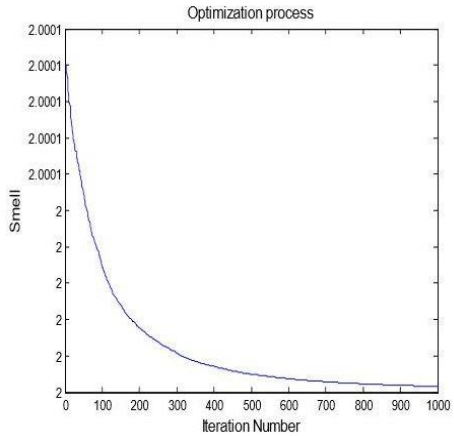


Figure 4: Best Fitness for IFOA [8] **Figure 5: Best Fitness for FOA [8]**

The above figures show the result by comparing the smell and iteration number, according to that the Improved FOA gives the Best Fitness value when compared to the FOA. Table 2 shows the performance of FOA and Improved FOA by using various function equations [18].

Table 2: Test Functions used in FOA and IFOA [18]

S.No.	Functions	m	y_i	y^*	$f(y^*)$
Fn1	$f(y) = \sum_{i=2}^{m} i y_i^2$	30	(-5.12, 5.12)	0	0
Fn2	$f(y) = \sum_{i=1}^{m} i(2y_1^2 - y_{i-1}^2)^2 + (y_1 - 1)^2$	30	(-10, 10)	0	0
Fn3	$f(y) = -(-0.5 \sum_{i=1}^{m} y_i^2)^e$	30	(-1, 1)	0	-1
Fn4	$f(y) = \sum_{i=1}^{m} (10^6)^{i-1/m-1} y_i^2$	30	(-100, 100)	0	0
Fn5	$f(y) = \sum_{i=1}^{m-1} (\sum_{j=1}^{i} y_j)^2$	30	(-100, 100)	0	0
Fn6	$f(y) = \max(\lvert y_i \rvert)$	30	(-100, 100)	0	0
Fn7	$f(y) = \sum_{i=1}^{m} \lvert y_i \rvert + \prod_{i=1}^{m} \lvert y_i \rvert$	30	(-10, 10)	0	0
Fn8	$f(y) = \sum_{i=1}^{m} (floor(y_i + 0.5))^2$	30	(-100, 100)	0	0
Fn9	$f(y) = \sum_{i=1}^{m} y_i^2$	30	(-100, 100)	0	0
Fn10	$f(y) = -20 \exp(-0.2\sqrt{1/n \sum_{i=1}^{m} y_i^2}) - \exp(1/m \cos(2\pi y_i)) + 20 + e$	30	(-32, 32)	0	0
Fn11	$f(y) = \sum_{i=1}^{m} \lvert y_i \sin(y_i) + 0.1\, y_i \rvert$	30	(-10, 10)	0	0
Fn12	$f_1(y, z) = 0.5 + \frac{\sin^2(\sqrt{y^2 + z^2}) - 0.5}{(1 + 0.001(y^2 + z^2))^2}$ Expanded to $f(y) = f_1(y_1, y_2) + f_1(y_2, y_3) + \ldots + f_1(y_m, y_1)$	30	(-100, 100)	0	0
Fn13	$f(y) = \frac{1}{4000} \sum_{i=1}^{m} y_i^2 - \prod_{i=1}^{m} \cos(\frac{y_j}{\sqrt{j}}) + 1$	30	(-600, 600)	0	0
Fn14	$f(y) = \sum_{i=1}^{m} (y_i^2 - 10 \cos(2\pi y_i) + 10)$	30	(-5.12, 5.12)	0	0
Fn15	$f(y) = 1 - \cos(2\pi\sqrt{\sum_{i=1}^{m} y_1^2}) + 0.1\sqrt{\sum_{i=1}^{m} y_i^2}$	30	(-100, 100)	0	0
Fn16	$f(x) = \sum_{i=1}^{m} (x_i^2 - 5*2 \cos(2\pi x_i) + 10)$ where $x_i = \begin{cases} y_i & \lvert y_i \rvert < \frac{1}{2} \\ round(2y_i)/2 & \lvert y_i \rvert \geq \frac{1}{2} \end{cases}$	30	(-5.12, 5.12)	0	0
Fn17	$f(y) = c \sum_{k=0}^{k_{max}} [a^k \cos(2\pi b^k (y_i + 0.5))] - m \sum_{k=0}^{k_{max}} [a^k \cos(2\pi b^k .0.5)]$ where a= 0.5, b=0.3, k_{max}= 30	30	(-0.5, 0.5)	0	0
Fn18	$f(y) = -\sum_{i=1}^{m} \{(-\frac{y_i^2 + y_{i+1}^2 + 0.5 y_i y_{i+1}}{8})^e \times \cos(4(\sqrt{y_i^2 + y_{i+1}^2} + \sqrt{0.5 y_i y_{i+1}}))\}$	30	(-5, 5)	0	1-n

Table 3: Comparing FOA & IFOA by its Mean value and Standard Deviation [18]

No.	Minimum	FOA		IFOA	
		Mean value	SD	Mean value	SD
Fn1	0	6.98e-04	1.54e-07	**6.75e-06**	5.58e-12
Fn2	0	5.93e-04	3.17e-08	**3.91e-06**	7.22e-12
Fn3	-1	-0.99	4.21e-11	**-1**	4.34e-15
Fn4	0	5.82	3.72e+01	**3.24e-0.2**	1.30e-04
Fn5	0	7.61e-02	2.19e-02	**8.13e-06**	1.04e-12
Fn6	0	1.75e-03	2.89e-06	**4.15e-05**	5.68e-10
Fn7	0	4.20e-02	7.97e-04	**3.15e-03**	8.49e-07
Fn8	0	6.40	9.29e+01	**0**	0
Fn9	0	1.03e-04	3.04e-08	**4.92e-07**	3.73-14
Fn10	0	7.78e-03	2.98e-05	**4.54e-04**	1.75e-08
Fn11	0	4.20e-03	1.36e-06	**3.01e-05**	7.58e-09
Fn12	0	2.42e-01	5.67e-02	**4.78e-04**	1.25e-08
Fn13	0	7.39e-07	1.41e-13	**9.97e-09**	1.24e-17
Fn14	0	9.13e-03	2.99e-05	**7.82e-05**	1.28e-09
Fn15	0	2.77e-03	5.16e-06	**6.41e-05**	2.28e-10
Fn16	0	1.52e-02	2.82e-04	**7.52e-05**	1.04e-09
Fn17	0	2.93	8.95e-01	**4.71e-01**	9.43e-04
Fn18	1-n	-29	4.85e-08	**-29**	1.32e-13

Now the [18] functions mentioned in the above table apply to both the algorithms; their mean and standard deviations are shown in Table 3.

From several results, the FOA gives good quality result for performance analysis during optimizing globally and also for parameter. Due to some difficulties faced by the researchers themselves use the improved form of FOA for occurring better results. From the experimental analysis, the above table clearly shows that the improved algorithm (IFOA) gives much better results than the FOA for the functions given in Table 3. But some of the application needs to set the appropriate parameter, still both algorithms give tremendous results for solving the optimization problem.

APPLICATIONS OF FOA

In this section, the applications of FOA, IFOA and MFOA (Modified FOA) and some hybrid works with FOA are also mentioned along with their area of usages. For FOA, Support Vector Machine (SVM-FOA)[6], Twin Support Vector Machine (TWSVM-FOA) [8], Travelling salesperson problem[9], Power load forecasting [10], PID controller tuning [11], Ship manoeuvring response model [12], Weibull Distribution Model P [13], The particle size distribution [14], Autonomous surface vehicles app [15], Path planning method for m.robot [16], etc. While in the case of IFOA (Improved FOA) the following application areas are used to get better results while compared with the original FOA. They are, Joint Replishment problem [17], continuous function optimization problems (IFFO) [18], Financial distress model [19], support vector machine for a least square improved FOA is used for the shearer cutting patterns are identified by using the signals occurred during vibrations [20], etc. By using MFOA(Modified FOA) the application areas are, Multidimensional knapsack problem (bFOA) [21], Financial distress forecasting(3D FOA) [22] PID controller tuning (MFOA) [23], Nonlinear functions solution(LGMS-FOA) [24], The bi-variable nonlinear function(G-FOA)[25], Key control characteristics (IFOA) [26], etc.,

There are some Hybrid works with FOA like Stock price prediction (FOAGRNN) [27], RBF neural network parameter settings (FOARBF) [28], Steam Turbines failure during the prediction researches (FOASVR) [29], Blind image restoration (FOA-LSSVR) [30], Slope stability analysis (FOAGRNN) [31], Evaluation of e-commerce website (FOARBF) [32], Fault diagnosis of fans (FOA-LSSVM) [33], etc.

CONCLUSION

This paper depicts the application of FOA in different domains and it can be hybridized with other machine learning algorithms to achieve better accuracy. The performance analysis of the FOA and its variants is done with the evaluation parameters. It concludes that the variants of the FOA performs better than the traditional FOA and it leads to develop new algorithms based on FOA and also its variants.

DECLARATION

The authors declare that the manuscript is original and is not published or communicated for publication elsewhere either in part or full.

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