Intelligent Water Drops Algorithm for Multimodal Spaces

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Abstract. This paper presents a new nature inspired Intelligent Water Drops (IWD) based algorithm for finding peaks in continuous multimodal optimization problems. Initially various conceptual similarities were identified between IWD algorithm and Genetic Algorithm(GA). Simultaneously applying IWD-Continuous Optimization(IWD-CO) algorithm and GA on a function in finding the global optima and found IWD-CO having faster convergence qualities. By taking this as basis, GA has been replaced with IWD-CO in a recently developed Modified Roaming Optimization(MRO) algorithm and applied to various benchmark functions and found drastic variation in convergence. Results are proving that replacing GA with IWD-CO can be a novel step in evolutionary based multimodal search algorithms.

Keywords: Genetic algorithm · Intelligent water drops algorithm · Roaming optimization · Modified roaming optimization · Evolutionary computation

1 Introduction

The nature besides the fact that it evolved a highly sophisticated life form of human being from an ape houses a wide range of life forms. Since the dawn of time, the whole of flora and fauna has gradually evolved and developed intelligent techniques for attracting the mates, finding food and all the basic needs. For many years researchers inspired from natural phenomenon and started imitating its processes to create meta-models. Nature inspired problem solving methods such as Evolutionary algorithms, Swarm based optimization algorithms etc., have been contributing much innovation in major areas like Robotics, Signal Processing etc. Most of them mainly contribute to optimization algorithms which can be defined as the process to make a system or design as effective or functional as possible by satisfying the given constraints. In these cases having secondary/multiple optimal solutions in hand may allow us to perform the required task. This has led to the development of multimodal optimization methodologies. In principle multimodal optimization is defined as finding multiple local optima(not necessarily

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equal). The major advantages of having all multiple optima are obtaining insight into the multimodal function landscape and alternative solutions can be chosen if the behavior of the constraints in the search space makes previous optimum solution unfeasible to implement. Some of the major areas where multimodal function optimization arises are localization, classification etc.

The Evolutionary Computation (EC) encompasses Genetic Algorithms (GAs), Differential Evolution (DE) etc. Traditional GAs are successfully identified the optima in the domain but they are incapable of maintaining rules of secondary importance. Attempts have been made to solve multimodal function optimization problems using a wide range of new approaches including Goldberg and Richardson's *sharing* [1], divides population using similarity of the individuals into possible solution spaces. DeJong's *crowding* [2], creates separate niches by replacing existing strings according to their similarity with other strings in an overlapping population. Rodica Lung and D. Dumitrescu's Roaming Optimization(RO) [3], divides the population into groups called sub-populations in a quest for multiple solutions. Besides sub-population concept, *Archive Test* plays major role in deciding the optimal solutions. RO has been successfully applied for detecting Nash equilibrium in multi-player games [4] and later Modified Roaming Optimization(MRO) [5] proposed by Chakravarthi J et al. added *Density based cluster removal step* for drastic decrements in running time of algorithm. This solved Inverse Kinematics(IK) problems of SCARA and PUMA robots as well. As there are ample of techniques for multimodal optimization, fastness became predominant factor of algorithms. In Genetic Algorithms, *mutation* helps to achieve the speed by having comparisons with previous results. Recently a novel evolutionary Intelligent Water Drops (IWD) algorithm [6], developed by Hamed Shah Hosseini, behaves similar to GA. Nagalakshmi et al. used IWD - Continuous Optimization(IWD-CO) algorithm [8] to solve Combined Economic and Emission Dispatch (CEED) [7] to find optimal cost values for 3, 6 plant power generating stations. Their work illustratively proving that IWD-CO has faster convergence compare to GA. In this paper, we have identified various similarities between IWD-CO and GA, simultaneously both have been applied to a continuous function in capturing it's global peak and various comparisons were made and later we replaced GA with IWD-CO in MRO [5] for finding peaks in multimodal benchmark test functions.

Rest of the paper has arranged in this way. Chapter-II explains IWD-CO algorithm and compares IWD-CO with GA, Chapter-III gives the proposed IWD algorithm for Multimodal Spaces, simulations and results are presented in Chapter-IV. Finally concluding remarks are given in chapter-V.

2 Intelligent Water Drops Continuous Optimization Algorithm

2.1 Basic IWD-CO Algorithm

In nature, water flow occurs in rivers and canals. Natural river paths have been created by swarm of water drops. Natural water drops have the tendency to flow from high terrain to low terrain. In order to reach an ideal path, water drops always try to change the real path which is having many twists and turns [8]. After observing natural phenomena of water flow and to mimic this process Hamed-Shah Hosseini [6] has created Intelligent Water Drops algorithm. The Intelligent Water Drops are given some properties of natural water drops such as,

- Water drop transfers some amount of soil when it moves from one place to another.
- While moving, soil of water drop increases and soil on the path will be decreased.

This nature-inspired evolution based Intelligent Water Drops are used to solve discrete and continuous optimization problems as well. The steps of Intelligent Water Drops-Continuous Optimization (IWD-CO) algorithm are as follows.

Problem Representation: Consider our problem is either to maximize or minimize an objective function $F(x_1, x_2, x_3, ..., x_M)$ where $x_1, x_2, x_3, ..., x_M$ are input parameters to the function. Mathematically, we can represent it as

$$max\ (or)\ min(F(x_1, x_2, x_3, ..., x_M)) \tag{1}$$

A directed graph with $(M \times P)$ nodes and $(2 \times M \times P)$ directed edges will be created. Between every adjacent nodes there will be two edges named 0 and 1. Here, M represents M-variable function and P represents the Precision which is the number of binary digits required to represent each variable. Initially same amount of soil is deposited on all the edges. Each IWD will carry some amount of soil with it and initially this value is kept zero and increases as it is passing through the nodes.

$soil(e_{i,i+1}(k))$ represents amount of soil present on k^{th} edge between i^{th} and $i+1^{th}$ node. k is an edge that can be either 0 or 1 and i is a node that ranges from 1 to $M \times P$. $soil_j^{IWD}$ represents soil possessed by j^{th} IWD. According to [6], various steps in IWD-CO algorithm are Edge Selection, Local soil updation, Mutation based local search and Global soil updation. Throughout this paper we used P = 32 and initial soil on the edges is 10000.

Edge Selection: Every IWD starts its journey from node 1 and finishes it by visiting the last node through edge selection process. Edge Selection for IWD is to choose an edge that is connected to next node. If the IWD is at node i then it selects the next edge $(e_{i,i+1})$ by choosing either 0 or 1 string between i and *i+1* nodes. The probability $P^{IWD}(e_{i,i+1}(k))$ for selecting an edge is given by

$$P^{IWD}(e_{i,i+1}(k)) = \frac{f(soil(e_{i,i+1}(k)))}{\sum_{l=0}^{1} f(soil(e_{i,i+1}(l)))} \tag{2}$$

where,

$$f(soil(e_{i,i+1}(k))) = \frac{1}{0.0001 + g(soil(e_{i,i+1}(k)))} \tag{3}$$

and

$$g(soil(e_{i,i+1}(k))) = \begin{cases} soil(e_{i,i+1}(k));\ if\ \ min_{l=0,1}(soil(e_{i,i+1}(l))) \geq 0 \\ soil(e_{i,i+1}(k)) - min_{l=0,1}(soil(e_{i,i+1}(l)));\quad else \end{cases} \tag{4}$$

Local Soil Updation: During visiting the nodes and selecting edges, the IWD updates the soil carrying by itself and removing some soil from the currently used edge. The soil of the IWD, $soil^{IWD}$ and soil of the visited edge, $soil(e_{i,i+1}(k))$ are updated by

$$soil(e_{i,i+1}(k)) = 1.1 * soil(e_{i,i+1}(k)) - 0.01 * \Delta soil(e_{i,i+1}(k)) \tag{5}$$

$$soil^{IWD} = soil^{IWD} + \Delta soil(e_{i,i+1}(k)) \tag{6}$$

where,

$$\Delta soil(e_{i,i+1}(k)) = 0.001 \tag{7}$$

Mutation Based Local Search: In IWD-CO mutations are nothing but changing the IWD position randomly in the search space by switching an edge in its path to avoid *premature* convergence. These mutations change the behavior of IWD path probabilistically. To improve the efficacy strong mutations have been introduced. Strong mutations accept the mutated fitness only if it is greater than previous fitness otherwise it remains unchanged.

Global Soil Updation: The Iteration best solution T^{IB}, among all IWDs is found at the end of current iteration by considering the best fitness value. In order to increase the probability for other IWDs to follow the best IWD's tour, soil on the respective edges are modified. This updation is given by

$$soil(e_{i,i+1}(k)) = min(max(TempSoil(e_{i,i+1}(k)), MinSoil), MaxSoil) \tag{8}$$

$$\forall\ e_{i,i+1}(k)\ \in\ T^{IB}$$

where,

$$TempSoil(e_{i,i+1}(k)) = 1.1 * soil(e_{i,i+1}(k)) - 0.01 * \frac{soil_{IB}^{IWD}}{(M * P)};\qquad \forall\ e_{i,i+1}(k)\ \in\ T^{IB} \tag{9}$$

$soil_{IB}^{IWD}$ represents the soil of best IWD. Here, Global soil updation is bounded by [MinSoil, MaxSoil]. Global soil updation will be done to the soil profile of the best IWD tour. This updation helps other IWDs to follow the best tour. In previous work [7], It is identified that IWD-CO has faster in convergence compare to GA and to check this, experiments have been done along with identification of various similarities between IWD-CO and GA explained in next section.

2.2 Comparison of IWD-CO with GA

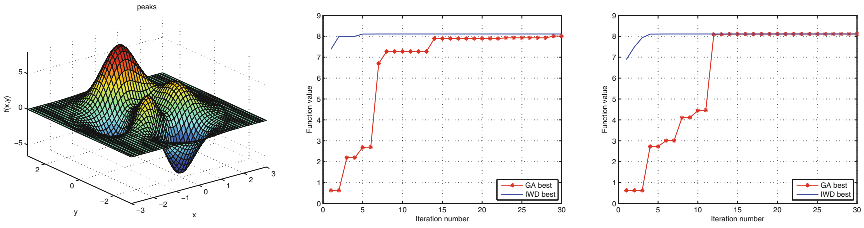
The main aim of this section is to show the similar behavior of the major steps in both GA and IWD-CO and to reasonably prove the faster convergence capacity of IWD-CO over GA which led us to replace GA part in Modified Roaming Optimization(MRO) algorithm with IWD-CO to improve the efficacy of the results by proposing a new hybridized algorithm called Intelligent Water Drops algorithm for Multimodal Spaces (IWD-MS).

Major Steps of GA and IWD-CO: Genetic Algorithm is a stochastic approach based on genetic parameters such as selection, crossover and mutation. In GA, the selection process means pairing of parent chromosomes and crossover means exchanging of information of chromosomes i.e. generating child chromosomes(Child population) from parent chromosomes. Mutations are nothing but switching the genes(binary bits), which helps in random exploration of search space. After completing above steps we use best half part of parent population and best half part of Child Population to create New population to persist the present best solution further. IWD-CO is based on Evolution parameters such as Global soil updation, Local soil updation and Mutations. In each iteration Global soil updation is carried out on the path of best IWD tour by decreasing the soil on the edges of that tour to increase the probability of next iteration IWDs to follow this path. Local soil updation is helpful in selecting the best edge i.e. to generate the best solution. Mutations in IWD-CO are called strong mutations for it's capacity of always increasing or maintaining the best fitness value. From these depictions we observe the similarities in the evolution parameters of IWD-CO and GA explained in next section.

Similarities in Evolutionary Parameters of IWD-CO and GA:

Global Soil updation - Selection: Global soil updation in IWD-CO behaves similar to the Selection process in GA. Global soil updation is done to sustain the best path by making new IWDs to follow it. Similarly GA uses Best chromosomes(parents having high fitness) in Selection process to sustain the best parental information for upcoming children population.
Local Soil updation - Crossover: Local soil updation in IWD-CO functions similar to Crossover in GA. Crossover is mating of parent chromosomes resulting the child population (New solutions). Similarly Local Soil updation in combination with Edge-Selection process produces the new solutions. Selected edge (New Solution) will have the cumulative effect of all the previously flown IWDs which changes the soil amount through Local soil updation. Here mating process among all previous IWDs is internally happening in their journey. So this internally mating process(Local soil updation and Edge selection) in IWD-CO is imitating the function of *crossover* as in GA.
Mutations in IWD-CO - Mutations in GA: Mutation step is same in both the algorithms but IWD-CO uses strong mutations. The mutations help in both GA and IWD-CO, to push the solution from the local optima towards the global optima. By the above observations, IWD-CO can be thought of analogous to GA.

Efficacy of IWD-CO over GA: To check the difference between the convergence capabilities of both algorithms, we considered peaks function f_2 in Table 1,



(a) 3 peaks function surface plot

(b) IWD-CO vs. GA while free mutations to GA

(c) IWD-CO vs. GA while strong mutations to GA

Fig. 1. (a) 3 peaks function surface plot (b) IWD-CO vs. GA while free mutations to GA (c) IWD-CO vs. GA while strong mutations to GA

shown in Fig. 1(a), which has its global optima value 8.1062 at (-0.0087,1.5813). We applied both GA and IWD-CO for that function by considering 6 initial solutions (also known as chromosomes in GA and IWDs in IWD-CO). Figure 1(b) shows the convergence in both algorithms. From this we can observe that IWD-CO has faster convergence and it is taking less number of iterations to capture global optima, whereas GA is taking relatively more number of iterations. Here the differences are considered as Strong mutations in IWD-CO and Free mutations in GA. But even if we apply strong mutations in GA, we can see the same response as shown in Fig. 1(c). Even in this case, IWD-CO is showing faster convergence. But there is an improvement in faster convergence of GA compare to free mutations in GA case but still relatively it is slower than IWD-CO. The reason for this effect is, in case of GA, the new chromosomes will be generated based on previous two parent chromosomes only. So the solution provided by new chromosomes will not have the effect of other chromosomes i.e. some of the new solutions may miss the effect of best parent too. Due to this reason the solution of present chromosomes may or may not support in updating the global solution for next iteration. If this happens so for all the chromosomes, the solution improvement may get delay in GA, even if we apply strong mutations as well. Whereas due to the Global soil updation on the best IWD tour (edges travelled by best IWD) will have effect in generating next best solution. So we can guarantee the improvement or consistency of best solution to next iteration.

Figure 2 shows the convergence of individual IWDs and chromosomes. Figure 3(a) shows parent and child best populations for all iterations in GA and Fig. 3(b) shows the IWD parent and child best solutions. From this, we can observe that next iteration best in IWD-CO has the cumulative effect of all the previously flown IWDs and best IWD from previous iteration. For instance we can observe this behavior from Fig. 2 which shows the individual IWD convergence where behavior of IWD4 is the evolved behavior of IWD-1, IWD-2, IWD-3. Similarly IWD-6 behavior is the evolved behavior of IWD-1 to IWD-5. New IWD always tries to follow the best IWD path, which can be observed from Fig. 4,

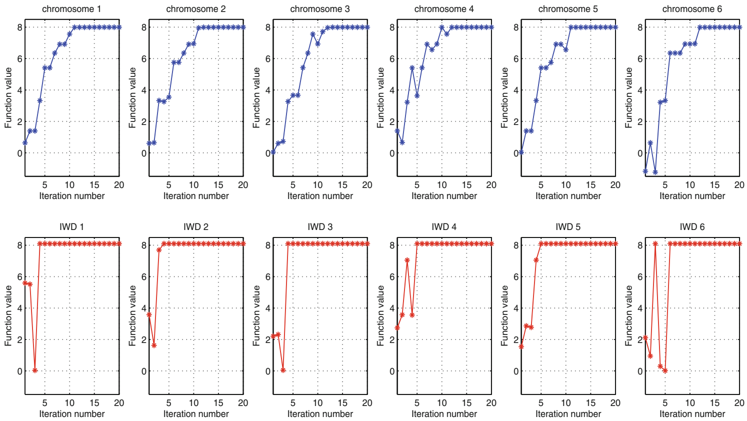
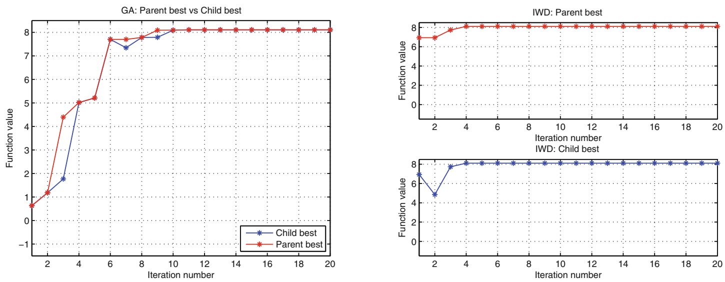


Fig. 2. IWD-CO vs. GA comparison of individual agents plot



(a) Parent best and Child best in GA

(b) Parent best and Child best in IWD-CO

Fig. 3. (a) Parent best and Child best in GA (b) Parent best and Child best in IWD-CO

which shows convergence of global best solution and particular IWD solution. Whereas GA has random effect in generating new (child) population. Strong mutations are making IWD-CO to find the solution with very less number of iterations because of it's ability to make the solution better or constant each time. From the above, we observe the analogy between GA and IWD-CO and also the efficacy of IWD-CO with respect to the convergence. We expect better results if we replace GA with IWD-CO in any of the evolutionary based parameters like *sharing* [1], *crowding* [2] and *sub-population* [3] for finding multiple peaks of a multimodal optimization problems. For this we considered recently developed MRO [5] and we come up with new hybridized algorithm Intelligent Water Drops algorithm for Multimodal Spaces (IWD-MS) explained in next section.

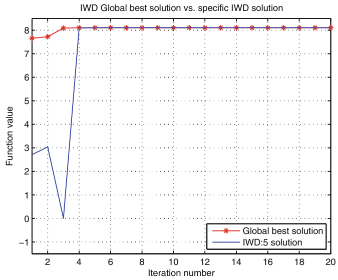


Fig. 4. Covergence plot of global best solution and specified IWD solution

3 Intelligent Water Drops Algorithm for Multimodal Spaces

This paper uses the concept of sub-population bound search for capturing multimodal peaks in a multimodal search space. It uses the concept proposed in Modified Roaming Optimization [5] by replacing GA with IWD-CO because of its fast converging capability seen in the Fig. 1, which is key for MRO algorithm. Figure 5, shows the block diagram of MRO algorithm [5]. IWD-MS algorithms has been created by including IWD-CO in place of GA in the MRO algorithm. Figure 6, shows the flowchart of IWD-MS algorithm. The steps in this algorithm are: Stability Measure, Roaming, Density based cluster removal and Archive test. These are explained below.

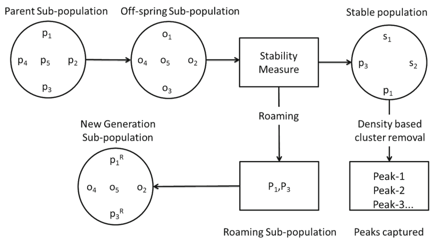


Fig. 5. Block diagram representation of MRO algorithm

Stability Measure: Best agent in each sub-population is regarded as potential optima. High stable potential optima contributes a near-optima point to the stable population. Stability measure determines, how better present sub-population compare to its off-spring sub-population. If a sub-population's stability exceeds a predefined threshold then it is considered as high stable population [3]. Let P_i and P_i^1 are i^{th} parent subpopulation and off-spring subpopulation respectively and x_i^* is potential optima of i^{th} subpopulation. Then we define a set 'B', containing the off-springs of P_i which are better than x^*.

$$B(x_i^*) = \left\{x \in P_i^1 : x > x_i^*\right\} \tag{10}$$

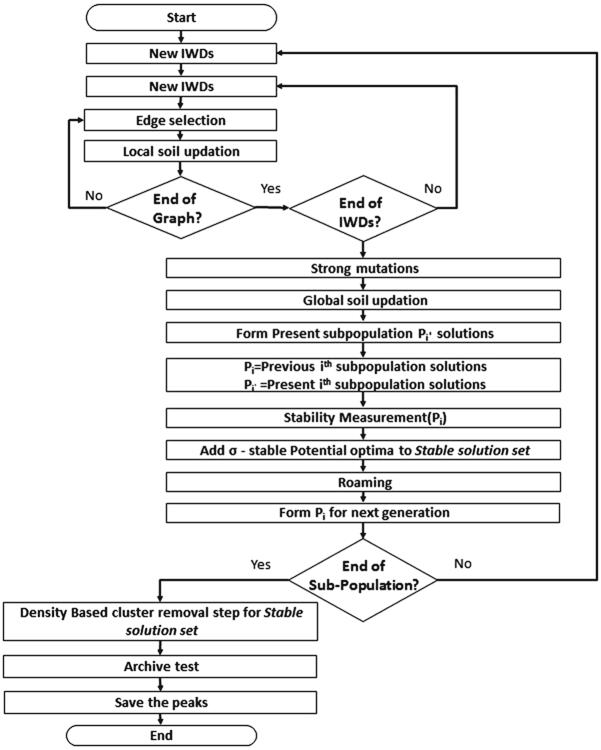


Fig. 6. Flow chart representation of IWD-MS

The stability measure of i^{th} subpopulation is defined as,

$$SM(P_i) = 1 - \{B(x_i^*)/|P_i|\} \tag{11}$$

In each iteration potential optima from the high stable populations will be saved.

Roaming: Roaming is necessary to search in the unexplored areas of the search space. The sub-populations having greater stability will contribute a potential optima and move to new areas in quest for other optima and mutation is used in roaming for the purpose of exploring new areas [3].

Density Based Cluster Removal Step: This step is applied on the *Stable Solution Set* which contains the points that are near to peaks. Plot of the *Stable Solution Set* depicts dense points around all the peaks as shown in Fig. 8. *Density based cluster removal step* identifies and saves a peak and removes all the points around that peak and it repeats the same procedure till the *Stable Solution Set* becomes empty. In the process of identifying the cluster, it uses the concept of density. Here, density is defined as,

$$density(x, \delta) = N/\delta \tag{12}$$

where δ is a small constant and N is no.of points in the range.

Archive Test: Archive test is applied on the final solutions obtained from Density based cluster removal step. It finds existence of a valley between every two solutions. If there is no valley between any two solutions then it's an indication that those two points belong to the same peak. Best solution among them is saved and the other one will be deleted. This step results final solutions(peaks) of the given multimodal function.

It has been proved that the MRO is more efficient with inclusion of *Density based cluster removal* step in reducing the total convergence time as compared to Roaming Optimization(RO) [3]. This paper focused on checking the capability of IWD-CO in capturing multiple peaks in a multimodal search space.

4 Simulations and Results

The proposed "Intelligent Water Drops Algorithm for Multimodal Spaces"(IWD-MS) has been tested on various benchmark test functions shown in Table 1, for its capability and efficacy in capturing multimodal peaks. Simulations conclusively show the better convergence times for all benchmark test functions compared to RO and MRO. Here, for illustrative purpose the Rastrigin benchmark function f_1 with 64 peaks in the range of [-4, 4] has been considered. Figure 7 shows the surface plot of Rastrigin function and Fig. 8 shows the surface plot with all stable points. Here, the proposed algorithm took 2.8216 sec. MRO and RO took 6.3165 and 96.434 sec respectively. Figure 9 shows 2-D plot of stable points after applying the step *Density based cluster removal* proposed in MRO. Figure 10 shows the Rastrigin function with final solutions of captured 64 peaks after application of *archive test*.

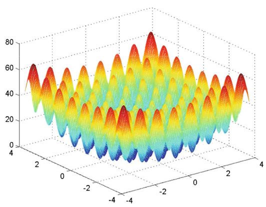


Fig. 7. Surface plot of Rastrigin function

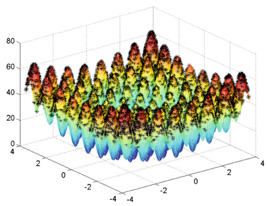


Fig. 8. Rastrigin function with all Stable points

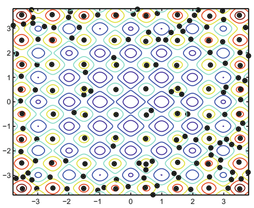


Fig. 9. 2-D plot of stable points after Density step

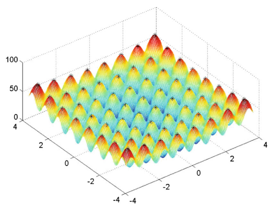


Fig. 10. Final plot with all peaks captured

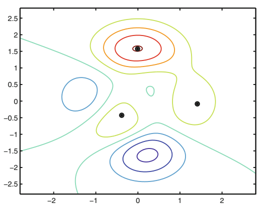


Fig. 11. 2-D plot of 3 peaks function

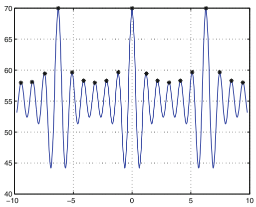
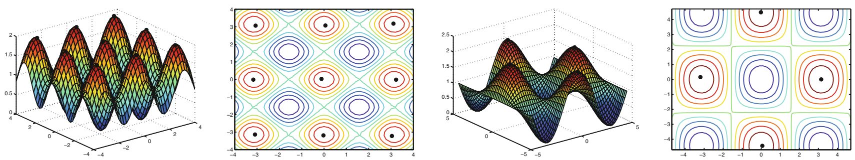


Fig. 12. 2-D plot of 19 peaks function

Table 1. Multimodal benchmark functions

Function	Profile	Range	Peaks
Rastrigin(2D)	$f_1(x,y) = 20 + \sum_{i=1}^{2} x_i^2 + (-1)^i * 10\cos(2\pi x_i)$	$[-5,5]^2$	100
Peaks	$f_2(x,y) = 3(1-x)^2 e^{-x^2-y^2} - 10((x/5) - x^3 - y^5)e^{-x^2-y^2} - (1/3)e^{-(x+1)^2-y^2}$	$[-3,3]^2$	3
Shubert(1D)	$f_3(x) = \sum_{j=1}^{5} j\cos((j+1)x+j)$	$[-10,10]^2$	19
Shubert(2D)	$f_4(x,y) = (\sum_{i=1}^{5} i\cos((i+1)x)+i) * (\sum_{j=1}^{5} j\cos((j+1)y)+j)$	$[-10,10]^2$	361
$f_5(x,y)$(2D)	$f_5(x,y) = \cos^2(x) + \cos^2(y)$	$[-4,4]^2$	9
Griewangk(2D)	$f_6(x,y) = \frac{1}{4000}\sum_{i=1}^{2} x_i^2 - \prod_{i=1}^{2}\cos(\frac{x_i}{\sqrt{i}}) + 1$	$[-4.8,4.8]^2$	4



(a) 3-D plot of f_5 (b) 2-D plot of f_5 (c) 3-D plot of f_6 (d) 2-D plot of f_6

Fig. 13. (a) 3-D plot of f_5 (b) 2-D plot of f_5 (c) 3-D plot of f_6 (d) 2-D plot of f_6

Comparison of Proposed algorithm with MRO and RO: It is already proved in the MRO [5] that it is taking less convergence time as compared to RO because of density step. After having conclusions with respect to IWD-CO vs GA, from chapter-II and from the above example on the Rastrigin function, it is showing even less convergence time with same number of peaks captured as compared to MRO and RO. To check the efficacy of the algorithm, it has been applied to Rastrigin function with various ranges for which the number of peaks also varies. Table 2 shows the comparison of proposed algorithm with MRO and RO in terms of their captured peaks and total convergence time. To validate the proposed algorithm for different characterized multimodal spaces, it has been applied to three more multimodal space functions which have larger variation in the number of peaks and search ranges. Figs. 11 and 12 show the 2-D plots of 3-peaks and 19-peaks functions at final iteration. Figure 13(a) shows the 3-D plot of f_5 and Fig. 13(b) shows 2-D plot with the captured peaks of f_5 and Fig. 13(c) shows the 3-D plot of f_6 and Fig. 13(d) shows 2-D plot with the captured peaks of f_6. Table 3 shows the comparison chart for all benchmark functions considered for testing and the efficacy of the algorithm with peaks captured and convergence time.

Table 2. Comparison of IWD-MS, MRO and RO for different ranges of Rastrigin function

Method	Range	Total Peaks	Detected Peaks	Time (sec)
IWD-MS	$[-1, 1]^2$	4	4	0.1796
MRO			4	0.6513
RO			4	1.322
IWD-MS	$[-2, 2]^2$	16	16	0.3136
MRO			16	1.8449
RO			16	8.513
IWD-MS	$[-3, 3]^2$	36	36	0.8108
MRO			36	2.7393
RO			36	24.623
IWD-MS	$[-4, 4]^2$	64	64	2.8216
MRO			64	6.3165
RO			64	96.434
IWD-MS	$[-5, 5]^2$	100	100	9.0472
MRO			100	16.1865
RO			100	368.217

Table 3. Comparison of IWD-MS, MRO and RO for different test functions

Function	Method	Detected Peaks	Total Peaks	Time (sec)
f_1	IWD-MS	100	100	9.0472
	MRO	100		16.1865
	RO	100		368.217
f_2	IWD-MS	3	3	0.1470
	MRO	3		0.3382
	RO	3		0.3891
f_3	IWD-MS	19	19	0.1083
	MRO	19		0.7295
	RO	19		3.189
f_4	IWD-MS	361	361	31.1359
	MRO	361		53.6204
	RO	361		732.5
f_5	IWD-MS	9	9	0.15
	MRO	9		2.71
	RO	9		4.42
f_6	IWD-MS	4	4	0.11
	MRO	4		1.12
	RO	4		1.62

5 Conclusions and Future Works

This paper has made its trails to show the possibility of using the Intelligent Water Drops algorithm, a nature inspired algorithm for multimodal spaces to capture peaks. The process of comparing IWD-CO with GA, shows slow convergence in GA in each iteration for both free and strong mutations and fastness as basis, later by replacing IWD-CO with GA in MRO algorithm for different test functions to capture multimodal peaks depicting that the convergence time with IWD-MS is very less compared to GA in MRO and RO. These results creating a new path in the evolutionary algorithms that GA can be replaced with IWD-CO in other themes like sharing, crowding which are also other techniques in multimodal optimization problems.

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