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A New Tool for Global Optimization Problems-Cuttlefish Algorithm

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***Abstract*—**This paper presents a new meta-heuristic bio-inspired optimization algorithm which is called Cuttlefish Algorithm (CFA). The algorithm mimics the mechanism of color changing behavior of the cuttlefish to solve numerical global optimization problems. The colors and patterns of the cuttlefish are produced by reflected light from three different layers of cells. The proposed algorithm considers mainly two processes: reflection and visibility. Reflection process simulates light reflection mechanism used by these layers, while visibility process simulates visibility of matching patterns of the cuttlefish. To show the effectiveness of the algorithm, it is tested with some other popular bio-inspired optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Bees Algorithm (BA) that have been previously proposed in the literature. Simulations and obtained results indicate that the proposed CFA is superior when compared with these algorithms.

***Keywords*—**Cuttlefish Algorithm, bio-inspired algorithms, optimization.

I. Introduction

GLOBAL optimization algorithms are usually categorized as deterministic and meta-heuristic [1]. Deterministic algorithms tend to use gradient technique and find greater use in solving unimodal problems, whereas meta-heuristic models tend to learn as they run. Therefore, meta-heuristic models are known to be more intelligent and adaptive. They are usually faster when locating a global optimum than the deterministic algorithms.

Most of the meta-heuristic algorithms such as Ant Colony Optimization (ACO) [2], Particle Swarm Optimization (PSO) [3], Bees Algorithm (BA) [4], etc. are bio-inspired which have previously been proposed in the literature. Recently, new meta-heuristic approaches are also presented by several researchers such as Collective Animal Behavior (CAB) algorithm [5], Gravitational Search Algorithm (GSA) [6], Bumble Bees Mating Optimization (BBMO) algorithm [7], Parliamentary Optimization Algorithm (POA) [8], Bat Algorithm (BA) [9] and Firefly Algorithm (FA) [10].

In this paper, a new meta-heuristic optimization algorithm that is inspired by the mechanism of color changing behavior of the cuttlefish is presented to find the optimal solution in numerical optimization problems. The proposed algorithm mimics the light reflection process through the combination of three cell layers, and the visibility of matching pattern process used by the cuttlefish to match its background.

The algorithm divides the population (cells) into four groups, each group works independently sharing only the best solution. Two of them are used as a global search, while others are used as a local search.

This paper is organized as follows: In Section II, cuttlefish skin components and color changing behavior are introduced. In Section III, the proposed CFA algorithm and its characteristics are described in detail. Section IV presents the experimental results and the comparative study. Finally, conclusions are given in Section V.

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II. Cuttlefish Skin Components

Cuttlefish [11], [12] is a type of cephalopods which is well-known for its abilities to change its color to either seemingly disappear into its environment or to produce stunning displays. The patterns and colors seen in cephalopods are produced by different layers of cells [13] stacked together including chromatophores, leucophores and iridophores. These layers are described as follows:

A. Chromatophores

Chromatophoresare groups of cells that include an elastic saccule that holds a pigment, as well as 15-25 muscles attached to this saccule [14]. When the muscles contract, they stretch the saccule allowing the pigment inside to cover a larger surface area. When the muscles relax, the saccule shrinks and hides the pigment [15].

B. Iridophores

Iridophores are found in the next layer under the chromatophores [16], [17]. Iridophores work by reflecting light [18] and can be used to conceal organs, as is often the case with the silver coloration around the eyes and ink sacs. Additionally, they assist in concealment and communication.

C. Leucophores

These cells are responsible for the white spots occurring on some species of cuttlefish, squid and octopus [14]. Leucophores are flattened, branched cells that are thought to scatter and reflect incoming light. In this way, the color of the leucophores will reflect the predominant wavelength of light in the environment [19]. In white light they will be white, whereas in blue light they will be blue.

III. Proposed Cuttlefish Algorithm

Chromatophores cells contain red, orange, yellow, black, and brown pigments. Besides, a set of mirror-like cells “iridophores and leucophores” allow cuttlefish skin to have all the rich and varied colors of its environment. The appearance of the cuttlefish thus depends on which skin elements affect the light incident on the skin. Light may be reflected by either chromatophores or by reflecting cells “iridophores or leucophores” or a combination of both and it is the physiological changeability of the chromatophores and reflecting cells that enable the cuttlefish to produce such a wide repertoire of optical effects. Fig. 1 denotes Cuttlefish skin detailing the three main skin structures (chromatophores, iridophores and leucophores) with two example states (a, b) and three distinct ray traces (1, 2, 3) that show the sophisticated means by which cuttlefish can change reflective color [20].

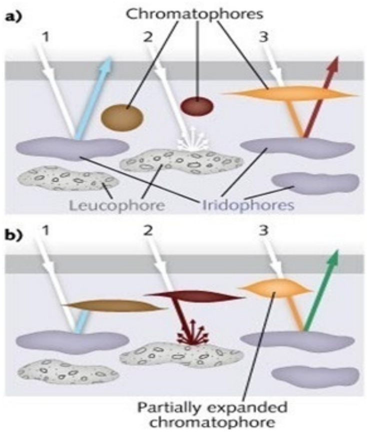

Fig. 1 Diagram of cuttlefish skin detailing the three main skin structures and three distinct ray traces

The proposed algorithm mimics the work of these three cell layers by reordering the six cases shown in Fig. 1 to be as shown in Fig. 2.

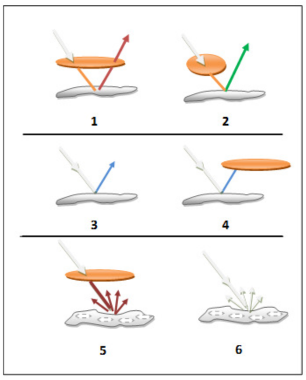

Fig. 2 Reorder of the six cases shown in Fig. 1

The general principle of the proposed CFA is shown in Fig. 3. The algorithm considers two main processes: *reflection* and *visibility*. Reflection process simulates the light reflection mechanism, while visibility simulates the visibility of matching patterns of the cuttlefish. These two processes are used as a search strategy to find the global optimal solution. The formulation of finding the new solution (*newP*) by using reflection and visibility is described in (1).

$$newp = reflection + visibility \tag{1}$$

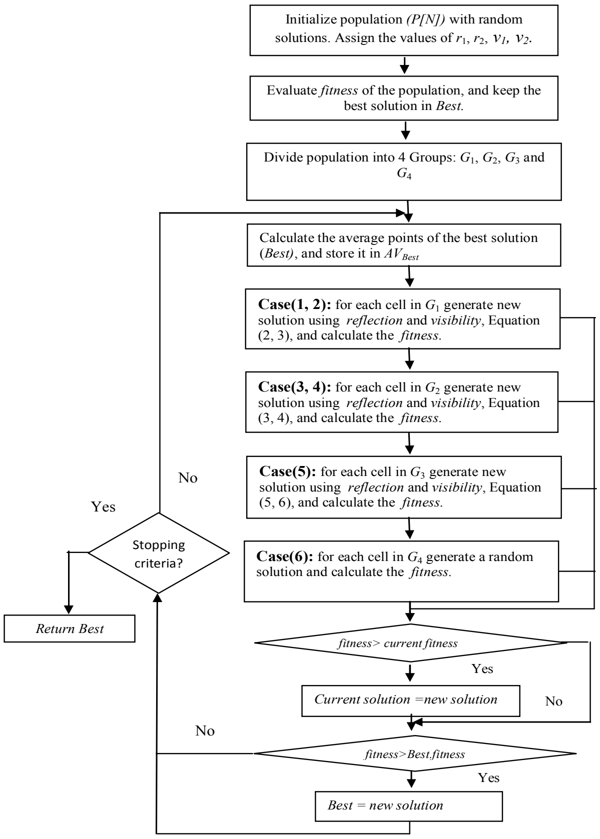

Fig. 3 The general principle of the proposed CFA

In order to simulate the stretch and shrink processes in chromatophors cells cases 1 and 2 in Fig. 2, we defined (2). This Equation is used to produce an interval that the chromatophors cells can use it to stretch and shrink their saccule. While the visibility of the matching background that used by cuttlefish is formulated in (3). This represents the deferent between best solution and current solutions.

$$reflection_j = R * G_1[i].Points[j] \tag{2}$$

$$visibility_j = V * (Best.Points[j] - G_1[i].Points[j]) \tag{3}$$

where, G_1 is a group of cells. i, is the i^{th} cell in G_1. *Points*[*j*] represent the j^{th} point of i^{th} cell. *Best.Points* represents the best solution points. R is a parameter that used to find the stretch or shrink interval of the saccule when the muscles of the cell is in contract or relax. V represents the visibility degree of the pattern. R and V are found as follows:

$$R = random() * (r_1 - r_2) + r_2 \tag{4}$$

$$V = random() * (v_1 - v_2) + v_2 \tag{5}$$

where, *random*() function is used to generate a random numbers between (0, 1). r_1, r_2, v_1, v_2 are four constant values specified by user such as (r_1=1, r_2=-1) and (v_1=0.5, v_2=-0.5).

These cases work as a global search uses the value of the current point to found new area around it. While the deference between the best point and the current point is used to gravitate produced point to the best solution.

In case (3 and 4), Iridophores cells are light reflecting cells and they are assisting in organs concealment. That's means the reflected color from iridophores cells around the organs is very similar to the color of organs. Thus the deference between the organs colors and the around cells color presents the visibility. This time the visibility will be used to calculate and simulate the interval of the stretch and the shrink processes. The simulation is based on the parameter V and the deference between the organs colors (*Best* points) and the current colors (current points). So the formulation of finding the visibility is remaining as it is in case (1 and 2).As a reflection, iridophores cells will reflect incoming light to cancel the organs. Since organs represented by the best solution, we assumed that the incoming color and the reflected color are the same, and they are represented by the best solution. Thus the formulation of finding the reflection is rewritten as in (6), and R is set to 1.

$$reflection_j = R * Best.Point[j] \tag{6}$$

Case (3 and 4) is used as a local search uses the difference between the best solution and the current solution to produce an interval around the best solution as a new search area.

In case 5, Leucophores cells are work as a mirror. In this way, the cells will reflect the predominant wavelength of light in the environment. In white light they will reflect the white, in brown light they will reflect brown and etc., In this case the light is coming through chromatophors cells with specific color. The reflected light is very similar to the light that is coming from the chromatophors cells. In order to cover the similarity between the incoming color and the reflected color, we assumed that the incoming color is the best solution (*Best*), and the reflected color could be any value around the *Best*. The interval that is used around the *Best* is produced by the visibility using the parameter V and the deference between the *Best* and the average value of the *Best*. The modification of finding the visibility is rewritten as follows:

$$visibility_j = V * (Best.Points[j] - AV_{Best}) \tag{7}$$

where, AV_{Best} is the average value of the *Best* points. While the reflected light from leucophores cells is represented by the *Best*. Thus the formulation of finding the reflection is remaining as it as in (6).

The algorithm uses case 5 as a local search, but this time the difference between the best solution points and the average value of *Best* points is used to produce a small area around the best solution as a new search area.

Finally, in case 6 the leucophores cells will just reflect the incoming light from the environment. This operator allows the cuttlefish to blend itself into its environment. As a simulation, one can assume that any incoming color from the environment will be reflected as it and can be represented by any random solution.

IV. Experiments and Validation

To test the performance of the CFA algorithm, Rosenbrock's valley function [21] with 16 dimensions is used. Fig. 4 shows a two-dimensional view of this function. This function has been frequently used to test the performance of the optimization algorithms and it has the following definition:

$$f(x) = \sum_{i=1}^{n-1}\left[100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2\right], \quad -2.048 \le x_i \le 2.048, \quad i = 1,\ldots,n \tag{8}$$
$$F\_\min(X) = 0, \qquad X(1,1,\ldots 1)$$

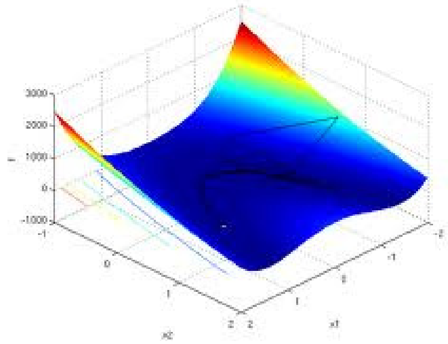

Fig. 4 Rosenbrock's valley function in 2D

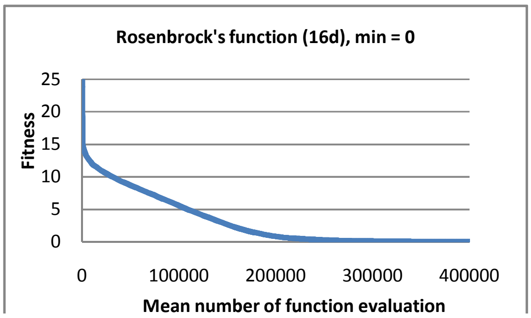

Fig. 5 Evolution of fitness with the mean number of function evaluation, Rosenbrock's function with 16d

Fig. 5 shows how the fitness values evolve with the number of function evaluations. The results are averages for 100 independent runs with population size equal to 60. It can be easily seen that after approximately 250,000 function

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evaluations, the CFA algorithm is able to find solutions close to the optimum.

We have also applied CFA to 12 well known test functions [21] listed in Table I in order to compare its performance with other well-known algorithms such as GA, PSO, and BA. For more detailed and additional results see [22].

TABLE I
TEST FUNCTIONS

Function Name	Interval	Function	Global Optimum
1. De Jong	[-5.12, 5.12]	$F\_\min = \sum_{i=1}^{d} x_i^2$	X(0, 0, …, 0) F = 0
2. Griewangk	[-600, 600]	$F\_\min = \sum_{i=1}^{d} x_i^2 - \prod_{i=1}^{d} \cos(\frac{x_i}{\sqrt{i}}) + 1$	X(0, 0, …, 0) F = 0
3. Ackley	[-32.768, 32.768]	$F\_\min = -a.\exp(-b.\sqrt{\frac{1}{n}\sum_{i=1}^{d} x_i^2}) - \exp(\frac{1}{n}\sum_{i=1}^{d}\cos(cx_i)) + a + \exp(1)$ a = 20, b=0.2, c=2π.	X(0, 0, …,0) F = 0
4. Rastrigin	[-5.12, 5.12]	$F\_\min = 10m + \sum_{i=1}^{d} [x_i^2 - 10\cos(2\pi x_i)]$	X(0, 0, …, 0) F = 0
5. Axis Parallel hyber-ellipsoid	[-5.12, 5.12]	$F\_\min = \sum_{i=1}^{d} (i * x_i^{\,2})$	X(0, 0, …, 0) F = 0
6. Martin and Gaddy	[0, 10]	$F\_\min = (x_1 - x_2)^2 + [(x_1 + x_2 - 10)/3]^2$	X(5, 5) F = 0
7. Rosenbrock's valley	[-2.048, 2.048]	$F\_\min = \sum_{i=1}^{d-1} [100(x_{i+1} - x_i^2)^2]$	X(1, 1) F = 0
8. Easom	[-100, 100]	$F\_\min = -\cos(x_i)\cos(x_2)\exp(-(x_1 - \pi)^2 - (x_2 - \pi)^2)$	X(π, π) F = -1
9. Shubert	[-10, 10]	$F\_\min = \sum_{i=1}^{5} i\cos((i+1)x_1 + i) \sum_{i=1}^{5} i\cos((i+1)x_2 + i)$	18 global min. F = -186.7309
10. Schwefel	[-500, 500]	$F\_\min = \sum_{i=1}^{d} [-x_i \sin(\sqrt{\lvert x_i \rvert})]$	X(420.9687, 420.9687) F= -418.9829n
11. Goldstein - Price	[-2, -2]	$F\_\min = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2] * [30 + (2x_1 - 3x_2)^2(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2]$	X(0, -1) F=3
12. Shekel's Fox-Holes	[-50, 50]	$F\_\min = \left[\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{2}(x_i - a_{ij})^6}\right]^{-1}$	X(-32, -32) F = 1

For genetic algorithms, we have used the real-value GA version [23] with elitism, with the mutation probability equal to 0.05, and the blending crossover [24] methods with the probability equal to 0.95, and roulette wheel selection. For PSO [25], the values of c_1 and c_2 are set to 1.49445 while the inertia factor ω is set to 0.729. For BA [4] and proposed CFA, Tables II and III, describe the parameter values that are used with different test functions, respectively. In Table II *n* represents the number of scout bees, *m* is the number of the best sites, *e* is the number of elite sites, *nsp* is the number of bees recruited for the *m* selected sites, *nep* is the number of bees recruited for best e sites. We run each algorithm for 100 times to make effective comparisons. All simulations have been carried out using C# on a Pentium Dual-Core CPU 2.20 GHz laptop, 2 GB RAM.

TABLE II
BEES ALGORITHM PARAMETERS

Function	*n*	*m*	*e*	*nsp*	*nep*	*ngh*
1	25	3	2	2	12	0.3
2	28	2	1	5	15	5
3	24	2	2	4	11	0.5
4	23	3	1	5	16	0.1
5	28	2	1	5	15	0.1
6	25	3	2	2	12	0.1
7	25	3	2	2	12	0.1
8	24	2	2	4	11	1
9	24	2	2	4	11	0.5
10	24	2	2	4	11	4
11	28	2	1	5	15	0.1
12	24	2	2	4	11	1

TABLE III
CFA ALGORITHM PARAMETERS

Function	r_1	r_2	v_1	v_2
1	1	-0.5	1	-1
2	0.4	-0.2	1	-1
3	1	-0.5	0.5	-0.5
4	1	-0.5	0.3	-0.3
5	1	-0.5	1	-1
6	1	-1	1	-1
7	1	-0.5	1.2	-0.2
8	2	-1	0.5	-0.5
9	1	-0.5	0.5	-0.5
10	3	-1	2	-2
11	0.5	-0.2	1	-1
12	1	-0.5	2	-2

To compare the speed of the proposed CFA with other algorithms, the number of function evaluations is fixed to 10,000 and the algorithm is stopped when the difference between the obtained minimum fitness and the global optimum is less than 0.001. Population size for all algorithms is fixed to 50.

Table IV describes the results that are obtained from the experiments. The results are averages for 100 independent runs to make effective comparisons. The form 968.5(100%) in Table IV means that the average number "mean" of function evaluation is 968.5 and the success rate of finding the global optima for this algorithm is 100%. The token (****) means that there is no obtained data with the current algorithm.

For the first five test functions 1, 2, 3, 4 and 5 in Table IV, we can see that the GA performs better than both PSO and BA. While PSO, is perform better than both GA and BA for functions 7, 8, 9, 10, 11 and 12. BA performs better than both GA and PSA with success rate 100% with function 6. From Table IV, it is also obvious that the CFA is faster and much superior to other algorithms in terms of accuracy and efficiency for all test functions.

TABLE IV
COMPARISON OF CFA WITH GA, PSA AND BEES ALGORITHM IN TERM MEAN NUMBER OF FUNCTIONS EVALUATION AND SUCCESS RATE, (100 RUN, 200 ITERATION, 10,000 FUNCTION EVALUATIONS)

Function	GA	PSO	BA	CFA
1. d=120	6962 (59%)	****	****	**1311 (100%)**
2. d=120	6889.5 (53%)	****	****	**3052 (100%)**
3. d=120	7426.5 (50%)	****	****	**2336.5 (100%)**
4. d=120	6919.5 (58%)	****	****	**2220 (100%)**
5. d=120	7116.5 (53%)	****	****	**1703.5 (100%)**
6. d=2	9901 (1%)	9707.5 (3%)	1448 (100%)	**236 (100%)**
7. d=2	9900.5 (1%)	1407.5 (100%)	7197 (46%)	**968.5 (100%)**
8. d=2	****	2094 (100%)	5868 (72%)	**335.5 (100%)**
9. d=2	****	3046 (100%)	****	**876 (100%)**
10. d=2	****	3622 (86%)	5385 (85%)	**560 (100%)**
11. d=2	5731 (72%)	1465 (100%)	9628.5 (7%)	**446 (100%)**
12. d=2	9999 (1%)	1447 (100%)	2753 (93%)	**893.5 (100%)**

V. CONCLUSIONS

In this paper, a new meta-heuristic optimization algorithm called Cuttlefish Algorithm (CFA) is introduced. The algorithm is inspired by the color changing behavior of cuttlefish to find the optimal solution. In this paper, the simulation of light reflecting and visibility of matching patterns processes of the cuttlefish are formulated. The results obtained by the proposed CFA in all cases provide superior results when compared with GA, PSO, and BA. As a future work, more study on CFA parameters is needed.

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