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Overview Of The Crocodile Optimization Algorithm

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Abstract
The natural hunting strategy of crocodiles has inspired the development of a novel population-based optimization algorithm known as the Crocodile Optimization Algorithm (COA). Crocodiles in the wild exhibit two distinct roles when hunting for fish: chasers and ambushers. Chasers use their powerful tail splashes to drive prey towards shallow waters without immediately catching them, while ambushers patiently wait in the shallows to swiftly snatch their prey. This intriguing natural behavior has served as a foundation for the COA algorithm. To assess the performance and effectiveness of the COA algorithm, it has been applied to various scenarios, including classical benchmark functions and four constrained engineering design optimization problems. These benchmark functions are commonly used to evaluate the efficiency and robustness of optimization algorithms.

Keywords: *optimization, prey,COA, benchmark functions.*

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I. Introduction

The Crocodile Optimization Algorithm (COA) is an innovative optimization approach inspired by the hunting tactics of crocodiles in their natural habitat. This algorithm, rooted in the strategic hunting behavior of crocodiles, has gained prominence in the realm of computational intelligence and optimization due to its ability to efficiently address complex problems spanning diverse domains.

COA takes its inspiration from the natural hunting techniques of crocodiles, particularly their distinct roles as chasers and ambushers. Chasers employ forceful tail splashes to drive prey towards shallower waters without immediate capture, while ambushers patiently lurk in the shallows, swiftly seizing their prey. This dualistic hunting strategy forms the fundamental basis of the COA. Operating as a population-based optimization algorithm, COA maintains a collective of potential solutions, represented as individuals, for a given problem. These individuals evolve iteratively to seek optimal or near-optimal solutions. The algorithm incorporates principles of natural selection and adaptation to enhance the quality of solutions within the population.

Crocodile Individuals are Within COA, individuals in the population serve as representations of prospective solutions to the optimization problem. Each individual encodes a potential solution using a specific representation format. The algorithm faithfully replicates the hunting behavior of crocodiles. Chaser individuals are responsible for steering prey towards a predefined target area, while ambusher individuals strategically a wait in this region to capture prey.COA incorporates mechanisms designed to attract prey (symbolizing solutions) towards regions of higher potential, where superior solutions are more likely to be discovered. Chasers and ambushers engage in collaborative efforts and healthy competition within the population, fostering a dynamic equilibrium between exploration and exploitation of solution spaces. The COA framework integrates a range of operators that facilitate the movement and adaptation of individuals, contributing significantly to the algorithm's efficacy.

The performance of COA is thoroughly assessed through comparative evaluations with other optimization algorithms, consistently demonstrating its competitiveness and prowess in terms of convergence speed and solution quality.

II. Related works

In this section, introducing the Crocodiles Hunting Strategy Optimization Algorithm (CHS), a vital component of the feature clustering process. CHS is integrated into a population-based algorithm, harnessing swarm intelligence to tackle optimization challenges [1]. Similar to other algorithms in this domain, CHS thrives on the exchange of information and the creation of an information flow through collaborative efforts, ultimately leading to the discovery of optimal solutions. This algorithm draws inspiration from the hunting behavior of crocodiles, a concept elucidated by Dinets[2].In the realm of crocodile hunting, two distinct roles are observed:

the chasers and the ambushers. Chasers, the larger among their peers, employ their formidable tails to create powerful splashes, herding fishes towards the shoreline but not catching them. On the other hand, ambushers, more agile and smaller, patiently wait in shallower waters, poised to snatch their prey [2]. As per Dinets' observations, crocodiles employ a sophisticated strategy for prey capture.

In the visual representation presented in Fig. 1, ambushers can be seen swimming in a circular pattern around their prey. They take turns cutting through the center of the progressively diminishing circle, expertly snatching the prey. The left section of Fig. 1 showcases the chasers' role, as they direct the prey towards the ambusher's attack zone. The subsequent section elaborates on how the behaviours of these two groups are translated into mathematical equations.

Fig. 1 Crocodiles behavior in hunting

Like other metaheuristic algorithms before entering the main phases, the initializing phase is done. In the initializing phase, several initial solutions are randomly generated. Indeed, these randomized solutions constitute the initial population of the crocodiles. These solutions are generated with uniform random distribution between the lower and upper bound[1].
These solutions are generated according to Eq. (1).

x = LB + rand × (UB − LB) (1)

After determining initial parameters such as the number of population, the number of max iteration, the lower bound of variables, and upper bounds of variables, random solutions (x) are generated based on Eq. (1) where LB and UB are lower and upper bound of problem, respectively. Also, random is a uniform random variable that is generated between zero and one. Then, these solutions are evaluated based on the objective function. In fact, in operators of CHS, the solutions are evaluated based on the objective function. Then, the best solution is selected between all generated solutions. The best solution has the minimum objective function value that is known as the best solution (xprey)[1].

Chasing the prey

In this section, we simulate the behavior of two distinct groups of hunters: the chasers and the ambushers. The chasers, being closer to the prey, constitute the first 50 percent of the solutions. On the other hand, the second half of the population consists of ambushers. It's important to note that ambushers generally exhibit higher values in the objective function compared to the chasers' group. This is because, during the initial phase, ambushers are positioned farther away from the prey compared to the chasers.

The selection of solutions is primarily influenced by the distance between the prey and the crocodiles[1]. Consequently, the chasers tend to have shorter distance values, while the ambushers have greater distances from the prey. As previously mentioned, the chasers are a distinct group of hunters. They closely follow the prey without attempting to catch it directly. Their main objective is to guide the prey towards the shoreline and shallow areas. To achieve this behaviour, we propose the use of Equations (2) and (3).

$$d = \left| x^{t}_{\text{prey}} - x^{i,t}_{\text{chaser}} \right| \quad \forall i \qquad (2)$$

$$\begin{cases} x^{i,t+1}_{\text{chaser}} = \left(x^{i,t}_{\text{chaser}} - \beta \bar{r} \cdot d \right) & \forall i d < \alpha \\ x^{i,t+1}_{\text{chaser}} = \bar{x}_{\text{rand}} - \beta \bar{r} \cdot d & \forall i d \geq \alpha \end{cases} \qquad (3)$$

Where x^t prey denotes to prey position at iteration *t*, $x^{i,t}$ chaser indicates the position of the crocodile *i*th at iteration *t*. x_{rand} is a random vector position, the coefficient β has a uniform distribution that changes between 0 and 3, and the vector *r* has a uniform distribution that is randomly generated in the range of 0 and 1. According to Eq. (2), *d* is a distance between the prey and chaser *i* th. According to Eq. (3), two states occur: first if $d < \alpha$, the above section of Eq. (3) is implemented which means that each chaser in the first group moved toward the prey with a positive coefficient and if $d \geq \alpha$, a random search is done. In brief, Eq. (3) shows that if the chasers are close to the prey, the attack is done by chasers otherwise, by a random approach close to the prey [1].

Attacking to prey

The final position of the prey is where the ambushers are waiting to catch the prey. Indeed, the ambushers camouflage in the final position and the chasers try to direct the prey to this place or the attacking area. In order to simulate the attacking phase, it is assumed that attackers are forced to update their position according to Eqs. (4), (5), and (6).

$$d = \left| x^{t}_{\text{prey}} - x^{i,t}_{\text{ambusher}} \right| \quad \forall i \tag{4}$$

$$A = \frac{\text{apc} + \text{apa} + \text{prey position}}{3} \tag{5}$$

$$\begin{cases} x^{i,t+1}_{\text{ambusher}} = \left(d.\cos(2\pi) + x^{t}_{\text{prey}}\right) & \forall id < \alpha \\ x^{i,t+1}_{\text{ambusher}} = \left(x^{i,t}_{a} - \beta\left(A - x^{i,t}_{a}\right)\right) & \forall id \geq \alpha \end{cases} \tag{6}$$

where xi ,t a shows the position of ambusher ith at iteration t and d denotes the distance between the ambushers and the prey. apc is the average position of chasers and apa is the average position of ambushers. Crocodiles update their position according to the positions of the prey or average of the position of all groups. In this way, if d < α, the above section of Eq. (6) is implemented that means that each ambusher swims around the prey with a rotational motion and if d ≥ α,ambushers update their position according to the average of the position of the all group of chasers, ambushers, and the prey. How to calculate the average is shown in Eq. (5).In designing a metaheuristic algorithm, the balancing of the two criteria of exploration and exploitation [3].

This enhances the algorithm's efficiency. Empirical evidence demonstrates that during the initial iterations, we should emphasize exploration, while in the final iterations, we should priorities exploitation. This implies that in the early iterations, we should explore different parts of the solution space, and in the later iterations, we should focus on refining the search around the optimal solution.

This pattern has been observed in the CHS algorithm. Consequently, during the exploitation phases, we introduce small mutations, and during the exploration phases, we implement longer mutations. The CHS algorithm is divided into two distinct phases, with each phase governed by a primary equation. Equation (3) serves as the main equation for the first phase, while Eq. (6) plays this role in the second phase.

In the initial iterations, the lower section of the main equations is more frequently executed. This is because, in most solutions, the distance between the best position and each solution exceeds α, leading to a more frequent execution of the lower section, which enhances the exploratory power. Conversely, in the later iterations, the upper section of the equations is predominantly executed. This is due to the fact that, in most solutions, the distance between the best position and each solution is less than α, thereby boosting the algorithm's exploitative capabilities[1].

Flowchart and pseudocode of the COA

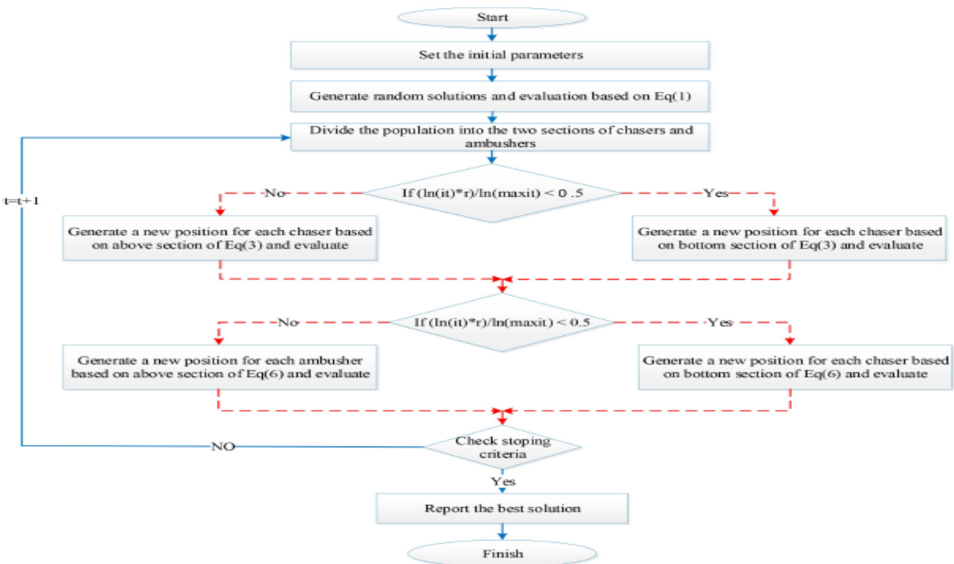

Fig. 2 Flowchat of the COA

```
For k=3 to 6
Set initial parameters
Initialize the population as cluster centers.
calculate the objective function of each cluster center according to Fig. 8
while stopping criteria is satisfied
  x_c chasers'population as first group of cluster centers
  x_a ambushers'population as second group of cluster centers
  x_prey = choose the best solution as the prey
  while (t<maximum number of iteration)
    For each cluster center in the chasers population
      Update C_chaser according to Eq. (7)
      Calculate the objective according to Fig. (8)
      update the best cluster center
    End for
    For each cluster center in the ambusher's population
      Update C_ambusher according to Eq. (8)
      Calculate the objective function of according to Fig. (8)
      Calculate the best cluster center
    End for
    t=t+1
  End while
End for
Report the best cluster center in each k
```

Fig. 3 Pseudocode of the crocodiles

III. CONCLUSION

In conclusion, the Crocodile Optimization Algorithm stands out as an innovative optimization method, inspired by the intricate hunting tactics of crocodiles. Its focus on a population-centric approach, faithful replication of hunting behaviours, and the synergy of cooperation and competition make it a compelling solution for addressing a wide range of optimization challenges across scientific, engineering, and interdisciplinary domains.

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