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SARDINE FEAST METAHEURISTIC OPTIMIZATION: AN ALGORITHM BASED ON SARDINE FEEDING FRENZY

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ABSTRACT

Many metaheuristics mimic biological interaction metaphors, such as ant colony, particle swarm, bee foraging, eagle predator behavior, and cuckoo brood parasitism, to solve complex optimization problems. Another type of biological interaction is commensalism, where one species obtains food from the other without harming or benefiting the latter. One of the great objective-driven commensalism phenomena that amazes scientists and has not yet been modeled is the sardine feast. In this study, we create an optimization algorithm, the sardine feast metaheuristic algorithm (SFMO), based on the ecological relationship between all predators involved in the feast. In this initial work, the algorithm is based on the behavior of dolphins and two types of sea birds, blue-footed boobies and brown pelicans, which prey on a school of sardines. We demonstrate the usefulness of the algorithm for solving several standard benchmark functions and compare the results with those obtained by using another metaheuristic algorithm, namely the Genetic Algorithm (GA), Bat-inspired Algorithm (BA) and Cuckoo Search (CS). The results of the tests show that the SFMO is better in terms of number of evaluations compared with the other algorithms. Further refinement of the model is needed to fully develop the algorithm.

Keywords: *Sardine Feast, Metaheuristics, Nature-inspired, Optimization*

1. INTRODUCTION

Swarm intelligence is inspired by the cooperation of collective homogeneous agents using only a few rules [1]. These natural behaviors involve similar interactions within a species or between particles that are collectively known as cooperation. For example, particle swarm optimization (PSO) is inspired by the social behavior of birds flocking or fish schooling and was developed by [2]. The bee algorithm (BA) mimics the foraging behavior of honey bees [3]. Other biological interactions, i.e., brood parasitism and predation, have been modeled in the cuckoo search [4] and the eagle strategy [5] algorithms, respectively.

Another known biological interaction is commensalism. It is a relationship where one species gets food from another species without either harming or benefiting the latter [6]. The non-cooperative between the species somehow solves their ultimate objective, e.g., to obtain food. The phenomena can be observed in the lifestyle of many livestock, insects, birds and plants. A great natural commensalism phenomenon that shows several animal species can co-exist optimally to hunt food is the sardine feast [7, 8].

The sardine feast is a spectacular marine event where millions of sardines are hunted by a teaming swarm of hungry predators while they make their migration from cold waters towards warm waters [9]. Among the contenders vying for a sardine meal are sharks, dolphins, seals, gannets, boobies, whales and even humans. The feeding frenzy is no usual line up and strike. Within a species, it is an intelligent and coordinated stake-out. However, between the species, there are no direct communications [7, 8, 10]. However, some species benefit from the others.

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In this study, we model a metaheuristic optimization algorithm inspired by the behavior of the species that prey on the schools of sardines. In our algorithm, each of the selected predators chooses one solution for a particular problem. Each type of predator has its own method of hunting. The algorithm will iterate until the objective function is satisfied. In nature, the feast will not stop until all the sardines are eaten. We compare the best solutions from our proposed algorithm with those obtained by using a known optimization algorithm, the cuckoo search (CS) algorithm.

Recent studies indicate that CS algorithms can out-perform particle swarm optimization, genetic algorithms and other conventional algorithms for many optimization problems, such as engineering problems [4]. This can be partially attributed to the broadcasting ability of the algorithm, which potentially provides better and quicker convergence towards the optimum. For that reason, we investigated the algorithm and reported our findings in [22]. Because the CS algorithm has performed the best to date, we compare our results from [4, 22] with those obtained using this proposed algorithm.

This paper aims to formulate a new algorithm, called sardine feast metaheuristic algorithm (SFMO), based on the interesting sardine feeding frenzy. We will first introduce the feeding behavior of several types of predator, and then formulate the algorithm, followed by its implementation. Finally, we will compare the proposed algorithm with other popular optimization algorithms and discuss our findings and their implications for various optimization problems.

In Section 2, we present the description of the imitated animals' behavior in the algorithm. We also elaborate on the proposed algorithm and its implementation. Then, we compare the results of our algorithm with those obtained using the cuckoo search (CS), bat algorithm (BA) and genetic algorithm (GA) in Section 3. We present the conclusions in Section 4.

2. MATERIALS AND METHOD

2.1 Animals' Behaviour in the Sardine Feast

In general, the feast can be divided into two stages. In the first stage, dolphins herd the school of sardines into a bait ball and prey on them. They use a combination of sonar and effervescence to drive and stun them into confusion. Then, in the second stage, when the bait ball is pushed up toward the ocean surface, the sardines are within reach of the seabirds. The seabirds join the feast by continuously diving into the ocean and emerging with their beaks full of panicked sardines. Some seabirds hit the sardines directly and others swim by, flapping their wings underwater, to chase their prey. The action continues until all sardines are captured.

The seabirds benefit from a school of sardines initially rounded up by the dolphins. Additionally, other dolphins benefit from the intense activity of the birds during feeding time, which helps them locate the school [11, 12]. The relationship between dolphins and seabirds in the Gulf of California is a form of commensalism [7] and is illustrated in Figure 1.

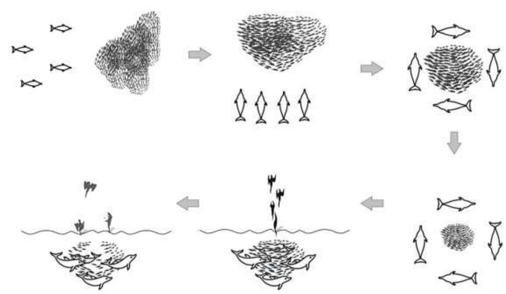

Figure 1. The relationship between dolphins and sea birds while preying on a school of sardines

In this initial work, although there are several predators involved in the feast, we only model several of them, i.e., dolphins and two types of seabirds, blue-footed boobies and brown pelicans. These predators are shown in Figure 2. These two types of seabirds are the most commonly observed birds associating with groups of feeding dolphins in the Gulf of California [7]. To describe the proposed algorithm more clearly, we will briefly review the foraging behavior of the selected predators in sub-sections 2.1.2 to 2.1.4. Then, we will outline the basic ideas and steps of the proposed algorithm in the following section. To start, we describe the behavior of the feast's target, the sardines.

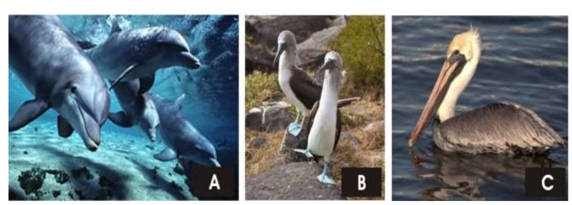

Figure 2. Predators involved in the feast: A. Dolphins, B. Blue-footed boobies, C. Brown pelicans.

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2.1.1 Sardines

The sardine (Sardinops sagax), or pilchard, is an ocean-going fish well known for traveling in large groups or schools [11] and is distributed throughout the world's oceans, i.e., on the coasts of California, Peru, Chile, Japan and South Africa [12]. Pacific sardines migrate to the Gulf of California from November to May and more frequently from December to January. During the winter season, millions of sardines travel along the eastern coast, spawn in warm waters, and return to their initial environment [9]. This phenomenon has become an important food source, and marine predators take advantage of this annual feast [7, 13].

2.1.2 Dolphins

Dolphins (Delphinus delphis) are known to be among the most intelligent of all the animals. Dolphins use a hunt feeding strategy with spread formations. They can detect a school of sardines using sonar [14]. When they approach the school, they will drive the fish towards a barrier and capture them with circle direction, driving the fish to the surface [15]. Each of the dolphins cooperates in the strategy to attack the sardines by circling the sardine school [13]. The dolphins start to tighten the encirclement, by forming smaller and smaller circles, to constrict the movement of their prey. They confuse the fish by diving from all directions into the school. This phenomenon is called bait ball (schooling sardines) and gives the advantage to other predators. The sardines are trapped and obstructed by the surface of the water. Other dolphins stay under the bait ball and slap their tails to create splash to maintain the perimeter of the bait ball while it is eaten from all sides [10, 13, 15]. Using this strategy, the dolphins can keep the bait ball at the surface, and other predators, such as the seabirds, can easily prey on the sardines.

2.1.3 Blue-footed boobies

Blue-footed boobies (Sula Nebouxii) specialise in eating school fish, such as sardines, anchovies, mackerel, and flying fish. They dive from altitudes of 20 to 25 m into the ocean and hunt alone, in pairs or in larger flocks. The lead bird sees a fish shoal in the water and gives a signal to the rest of the group. The signal tells the rest of the group to dive in unison to catch the fish [16]. During the feast, blue-footed boobies start diving toward the core of a bait ball when it is in their sights [7]. To dive, they tilt downward, fold back their wings, and pierce the water's surface headfirst [17]. There are two dive types recognized: V-shaped dives, when the birds dive to a maximum depth and immediately return to the surface, and U-shaped dives, when horizontal or zigzagging displacement occurs at the maximum dive depth [18]. The majority of immersions consist of V-shaped dives in which the boobies reach their maximum depth and then immediately ascend to the surface.

2.1.4 Brown Pelicans

Brown pelicans (Pelecanus Occidentalis) are very gregarious birds and feed using plunge diving. The brown pelican is the only pelican species that dives for fish. They fly slowly at approximately 9 meters above the water surface, and upon sighting prey, they suddenly check their flights and dive bill first into the water [19]. They hunt inactively by scooping up fish while swimming on the surface of the water. They need more energy to dive from higher heights than they do to dive short distances when prey is in abundance [20]. During the feast, pelicans take their portions by scooping up the scattered sardines around the bait ball [27]. The pelican's pouch expands as it fills with water during the dive. If the dive is successful, the pelican keeps its beak closed, slowly draining the water before flicking its head and swallowing the prey. However, if no prey is caught, its beak is left open and the pouch is quickly drained [21].

2.2 Sardine Feast Metaheuristic Algorithm

The new sardine feast metaheuristic algorithm is conceptualized based on the commensalism foraging behavior of the dolphins, boobies and pelicans in catching a bait ball of sardines. For the initial algorithm and simplicity, we use the following five assumptions:

i. The bait ball represents the main target or attraction of all predators. Most of the sardines are located at the heart of the bait ball. Once it is targeted, it will move, either trying to disperse or swaying naturally with the currents. The size of a bait ball is called the bait ball size (*bbs*).

ii. There are no interactions or coordination between the predators. They prey differently. Their source of reference is the bait ball center.

iii. The behavior of the predators are:

a. Dolphins: Search the ocean space for a school of sardines. Once spotted, they encircle the sardines into a bait ball. They only circle the bait ball, i.e., outside its

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bbs, until the feast ends. However, in the real world, in addition to circling, each individual member takes turns ploughing through the bait ball and feeding on the more compacted shoal.

b. Boobies: Plunge dive at approximately the centre of the bait ball. Their diving area is called the diving search spot (*dss*).

c. Pelicans: Scoop up sardines in the bait ball. Their scooping area is called the scooping search spot (*sss*).

The *bbs*, *dss* and *sss* are illustrated in Figure 3 in relation to the bait ball.

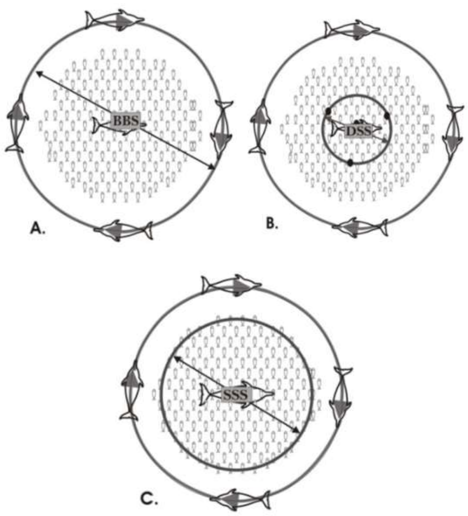

Figure 3. A. Bait ball size by dolphins (bbs), B. Diving search spot by boobies (dss), C. Scooping search spot by pelicans (sss).

iv. Each predator is represented as a "solution". In solving an optimization problem, each predator is replaced with a solution of the problem. However, the solution (center of the bait ball) is dynamic, and the predator (based on the current position of the bait ball) must correct their position.

v. To mimic the real feast, we divide the algorithm into 2 stages as follows:

a. Stage 1: Dolphins searching the ocean space for a school of sardines. They will stop searching once a member finds a good school, defined by a pre-set threshold value, set as the *bss*.

b. Stage 2: Boobies and pelicans start plunge diving and scooping, respectively. The dolphins encircle the bait ball until the algorithm ends.

To resemble the dynamics of the feast in our algorithm, in the first stage, the dolphins always move to the best position to trap the school of sardines. The best position is the dolphin which has the nearest position to the school of sardines (the optimum solution among current solutions at hand). In the second stage, we assume that the leader of the seabirds (boobies and pelicans) has found the current bait ball center (optimum point), and other birds move towards it by correcting their position according to *dss* and *sss* constraints. If any of them finds a point better than the current leader, it becomes the leader in the next iteration. The dolphins will keep searching out of the ring of siege (*bbs*) to keep bringing sardines back into the bait ball. If any of the dolphins finds a point better than the current leader, it also can become the leader in the next iteration. In the metaheuristic, the concentrated plunge diving of the boobies resembles intensification, while loosely searching outside the bait ball by the dolphins can be considered diversification.

Based on the above description, Figure 4 shows the flow chart of the proposed algorithm.

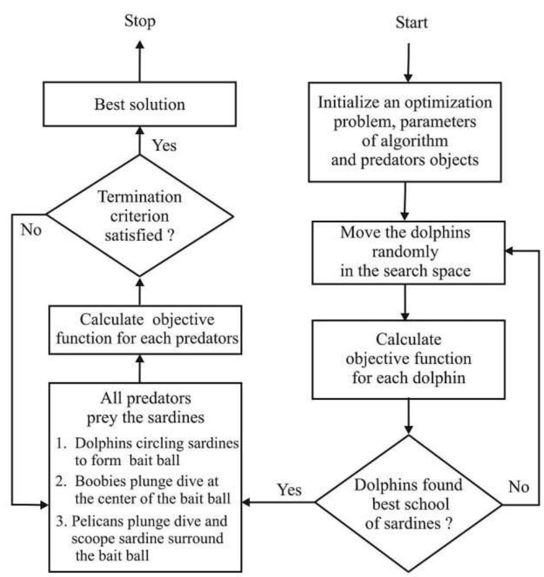

Figure 4. Flow chart of the sardine feast algorithm

The details of each step are:

- Step 1: Initialize the optimization problem, algorithm parameters and predators' objects. The parameters are:
  - *D*, number of dolphins
  - *B*, number of boobies
  - *P*, number of pelicans
  - *bbs*, bait ball size
  - *dss*, diving search spot
  - *sss*, scooping search spot
  - *bss*, best sardine shoal
- Step 2: Move all dolphins in the search space randomly.
- Step 3: Evaluate the objective function for each dolphin. Dolphins that are near the objective function have targeted values that are among the best. Sort their performances.
- Step 4: Have any of the dolphins found the best sardine shoal (*bss*)? This question is evaluated based on whether the performance of the best dolphin goes beyond a predefined threshold value. If yes, the dolphins have successfully trapped the sardines into a bait ball; proceed to Step 5: if not, go back to Step 2.
- Step 5: Move all predators to prey on the sardines in the search space according to their specialized preying techniques. The dolphins keep circling outside the bait ball using *bbs* as the reference. The boobies plunge dive in close proximity to the center of the bait ball using the *dds* as the reference. The pelicans scoop sardines around the bait ball at the surface of the water using the *sss* as a reference.
- Step 6: Calculate the objective function for each of the predators, and sort their performance. Set the best predator values as the reference for the next iteration's *bbs*, *dds* and *sss*.
- Step 7: Do the best predators' values meet the stop conditions? If yes, go on to Step 8; otherwise, go back to Step 5.
- Step 8: The computation is terminated. Report the best solution values of the objective function and its performance measurements.

2.3 Implementation and Benchmarking for the Algorithm

The computational procedures described above have been implemented in a Matlab program on an Intel Core™ i3 2.27 GHz computer. In this study, our proposed algorithm is tested to solve different unconstrained and constrained standard benchmark functions from the literature [22, 24, 26] to demonstrate its efficiency and robustness.

We selected nine benchmark functions, which are the Shubert, Rosenbrock, Easom, and Michelewicz functions. The details are presented in Table 1. Output from the algorithm is validated with the analytical or known solutions.

2.4 Experiments

After implementing the algorithms using Matlab, we performed extensive simulations. Each benchmark function was run 100 times to perform meaningful statistical analyses. The algorithms stop when the variations of the function values are less than a tolerance of 10−5. There are many ways to compare algorithm performance, and two possible approaches are to compare the number of function evaluations for a given tolerance or accuracy or to compare the accuracies for a fixed number of function evaluations. In this study, we used the first approach.

In all of our simulations, we use $D = 4$, $B = 4$, and $P = 3$. Other parameters are set as shown in Table 2. We selected those parameters using the trial-and-error approach. Parameters of the compared algorithms are collected from their respective papers.

Table 1. Benchmark functions

Function	Function	Bounds	Global Min
Shubert (Dim: 2)	$f(x) = \left(\sum_{i=1}^{5} i\,cos\big((i+1)x_1 + 1\big)\right)\left(\sum_{i=1}^{5} i\,cos\big((i+1)x_2 + 1\big)\right)$	$x_i \in [-10, 10]$, for all $i = 1, 2$	−186.73
Rosenbrock (Dim: 2)	$f(x) = \sum_{i=1}^{d-1} 100.(x_{i+1} - x_i^2)^2 + (1 - x_i)^2$	$x_i \in [-2.048, 2.048]$ for all $i = 1, 2$	0
Easom (Dim: 2)	$f(x) = -\cos(x_1)\cos(x_2)\exp(-(x_1-\pi)^2 - (x_2-\pi)^2)$	$x_i \in [-100, 100]$, for all $i = 1, 2$	0
Michalewicz (Dim: 16)	$f(x) = -\sum_{i-1}^{d} \sin(x_i).\left(sin\left(\frac{i.x_i^2}{\pi}\right)\right)^{2-m}$; m = 10	$x_i \in [0, \pi]$, for all $i = 1, \ldots, d$	0

Table 2. The experimental parameters of the proposed algorithm

Function	*bbs*	*dss*	*sss*	*bss*
Shubert	1.0	10^{-2}	0.1	10^{-5}
Rosen-brock	1.0	10^{-2}	1.0	10^{-3}
Easom	1.0	10^{-2}	1.0	10^{-3}
Michale-wicz	1.0	10^{-2}	1.0	10^{-3}

3. RESULTS

The results are summarized in Table 3 where the global optima are reached. The success rate of finding the global optima for this algorithm is 100% out of 100 attempts. We can see that the proposed algorithm is extremely efficient at finding the global optima with high success rates. Using our algorithm, each function evaluation is virtually instantaneous on a modern personal computer. Generally, for all the test functions, our algorithm outperformed the GA, BA and CS algorithm.

Table 3. Results of applying the sardine feast and other methods to solve the benchmark functions.

Function		GA [4, 28]	BA [4]	CS [4, 22]	Proposed Algorithm
Shubert	Mean	54,077	11,925	9,107	2,973
	Stdev.	4,997	4,049	2,497	1,494
	Success rate	89%	100%	100%	100%
Rosenbrock	Mean	55,723	7,923	5,939	4,064
	Stdev.	8,901	3,293	1,495	1,552
	Success rate	90%	100%	100%	100%
Easom	Mean	19,239	7,532	5,984	5,393
	Stdev.	3,307	1,702	2,064	4,888
	Success rate	92%	100%	100%	100%
Michalewicz	Mean	89,325	4,752	2,842	957
	Stdev.	7,914	753	678	661
	Success rate	95%	100%	100%	100%

4. DISCUSSION

The behavior of the algorithm can be seen by locating every predator during the algorithm execution. In the case of Michalewicz function, its landscape is shown in Figure 5. The global optimum values can easily be found using our algorithm, and the results are shown in Figure 6, where the locations of the predators are also marked using red circles for the blue-footed boobies, black crosses for the brown pelicans, blue diamonds for the dolphins and black rectangle for the global minimum.

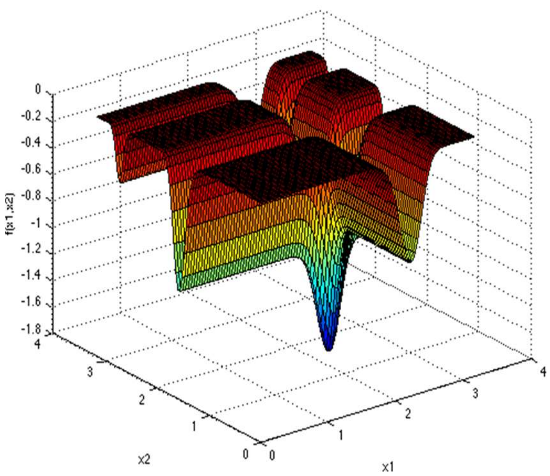

Figure 5. The Michalewicz Landscape Function

In Figure 6(A), the sardine feast algorithm occurs at level 1, where dolphins explore the search space to find a bunch of sardines. Once they find the best position, dolphins around the school of sardines and start make the bait ball of sardines and shape them. Then, in iterations 2, the stage 2 begin, the sea-birds (bobbies birds and brown pelicans) begin to plunge diving on bait ball center as seen in Figure 6(B). Bait ball of sardines is a group of dynamic, so that predators need to correct their position, while the dolphins will continue to move to bring the sardines into a bait ball and moved toward the optimum point as seen in Figure 6(C). This event continues to be the optimal point, as in Figure 6(D).

The dolphins are also distributed at different (local) optima in the case of multimodal functions. This means that the algorithm can find most of the optima simultaneously if the number of predators is much greater than the number of local optima. This advantage may become more significant when dealing with multimodal and multi objective optimization problems.

5. CONCLUSION

In this study, we have formulated a new metaheuristic algorithm, the sardine feast metaheuristic algorithm, based on the commensalism observed when various predators prey on a school of sardines. Foraging behavior of predators such as dolphins, boobies and pelicans are studied. The proposed algorithm was validated and compared with the GA, BA and CS algorithms. Simulations and comparisons show that our proposed algorithm is superior to the CS algorithm for all objective functions. This result is positive because there are several specialized predator behaviors that make the diversification and intensification of the algorithm possible. In addition, the early work of the dolphins reduces the search time.

However, in term of limitation, our algorithm requires few parameters that need to be tuned. This drawback means that we have to fine-tune these parameters for a specific problem. Further studies will focus on designing the algorithm with fewer parameters by studying the sensitivity of the parameters and their possible relationships with the convergence rate of the algorithm.

This potentially powerful algorithm can easily be extended to solve multi-objective optimization applications with various constraints. In addition, incorporating other sardine feast predators such as sea lions, sharks, whales and gannets would be interesting to explore. Hybridization with other popular algorithms, such as the particle swarm optimization, and integration of levy flight component such as in [4, 22] will also be potentially fruitful.

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Conflict of Interest

The author(s) declare(s) that there is no conflict of interest.

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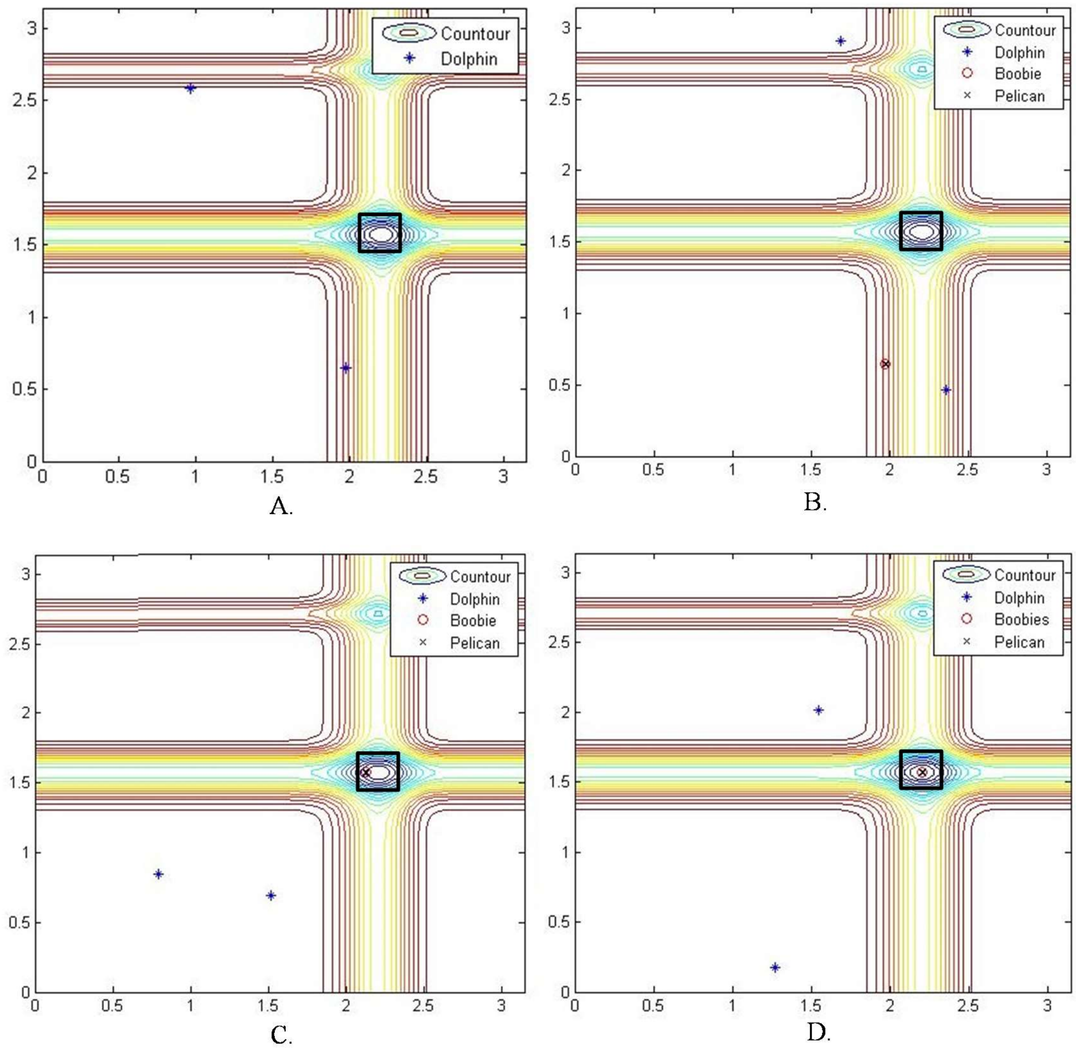

Figure 6. The locations of the predators. A. at iteration 1, B. iterations 2, C. iterations 10 and D. iterations 66.

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