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Digestion Optimization Algorithm: A Bio-inspired Intelligence Approach for Global Optimization Problems

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Abstract

Digestion Optimization Algorithm is a biologically inspired metaheuristic method for solving complex optimization problems. The development of the algorithm is inspired by studying the human digestive system. The algorithm mimics the process of food ingestion, breakdown, absorption, and elimination to effectively and efficiently search for an optimal solution. This algorithm was tested for optimal solutions on seven different types of optimization benchmark functions. The algorithm produced optimal solutions with standard errors, which were compared with the exact solutions of the test functions.

1 Introduction

The roles of optimization cannot be swept aside in human day-to-day activities. At every point in time, decisions are made in different sectors of life such as medicine, finance, engineering, and the general sciences. These decisions could involve the management of resources, finding a control strategy, reducing cost, and maximizing profit under certain conditions. These, to mention a few, are the importance of optimization.

Optimization can be defined as the act of finding possible solutions to a given problem. It is the science of exploring diverse mathematical approaches, computing schemes, heuristic and metaheuristic processes. A number of optimization methods have been developed using traditional approaches. Although traditional methods of optimization have been reported to have accurate convergence rates, these techniques are known to have limitations such as trapping solutions in local minima, the computational cost of gradient functions for gradient-based methods, and limited directional search strength, among others (Faramarzi et al. [7]).

These limitations have triggered further research and the development of optimization methods using

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modern techniques, heuristic, and metaheuristic processes. Modern methods of optimization are the most widely used methods in solving optimization problems. Biologically inspired processes have become an interesting area in the design of modern optimization tools. Genetic Algorithm (GA), developed by Holland [9], and Differential Evolution Method (DE) by Storn and Price [15], have motivated the development of modern optimization algorithms in recent years.

Some of the developed algorithms include, but are not limited to, Firefly Algorithm (FA), developed from studying the nature of fireflies and their light production by Yang [16]; Wind Driven Optimization (WDO) by Bayraktar et al. [4]; Brain Storm Optimization (BSO) by Shi [14]; Flower Pollination Algorithm by Yang [17]; Mosquito Flying Optimization Algorithm by Alauddin [3]; Pollination Intelligence Algorithm by Ejieji and Akinsunmade [6]; the African Vulture Optimization Algorithm by Abdollahzadeh et al. [1]; Jaya-based Algorithm by Akinsunmade and Aina [2]; the Sea Horse Optimization Algorithm, which draws inspiration from the natural behaviors of seahorses, by Zhao et al. [19]; and Secretary Bird Optimization Algorithm by Fu et al. [18].

Despite all the significant achievements recorded in the development of metaheuristic-based algorithms, the no-free-lunch theorem holds for these algorithms. Some find the best solution in certain applications; however, they may not perform well in another class of problems. In this paper, a new class of biologically inspired, intelligence-based optimization technique called the Digestion Optimization Algorithm is presented.

2 Digestion Optimization Algorithm

Digestion is the breaking down of food into smaller molecules. This process is carried out in humans by the digestive system, beginning in the oral cavity and then passing through the esophagus, thereafter involving other processes in the pancreas, stomach, intestines, liver, and anus (Sensoy [13]).

These organs work hand in hand to process food into energy for the benefit of the human body. The process of digestion can be grouped into four stages: ingestion, breakdown, absorption, and elimination. Food substances are introduced into the body through the mouth by mastication, with the help of the tongue and the salivary glands, which lubricate and moisten the substances before they are transferred into the food pipe. The absorption process takes place in the small intestine; this process involves the extraction and grouping of essential nutrients. Excess water from indigestible food substances is transferred to the large intestine (Ketel et al. [11]). The final process of digestion is excretion. This is the total elimination and removal of indigestible food substances; waste by-products from the body are excreted from the body system. These processes (ingestion, breakdown, absorption, and elimination) are modeled into mathematical equations to provide a step-by-step instruction system for problem solving in this order.

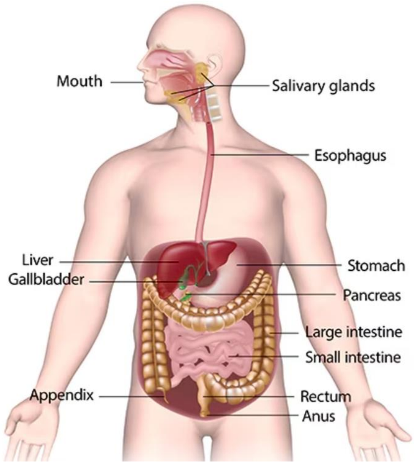

Figure 1: Human Digestive System

i ingestion (input stage)

ii breakdown (the processing stage)

iii absorption (the analysis stage)

iv elimination (convergence stage)

Ingestion Stage

This is modeled as the initial stage of iteration. A population of candidate solutions (S_p) in the form of food particles is randomly generated along with their associated microbes (M_p).

Breakdown Stage

A crossover operator (C) is introduced to help pair solutions and create new solutions. This process helps break down the solution into smaller components.

Absorption Stage

The nutrient value of each solution, based on its fitness (F) and microbiome (M), is calculated. The nutrient value is then assigned to each solution according to the nature of its fitness. At this stage, the nutrient value is modified based on the solutions, in order from highest to lowest. This action updates the level of the microbes (M_p).

Elimination Stage

This is termed the convergence stage. The fitness solutions are sorted from the best to the worst. The worst solution is considered waste and is completely eliminated.

The above process is presented in the algorithm below:

Digestion Algorithm

1. Define the population size, crossover probability, and size of the microbiome as N, P_c, and M, respectively. Set the fitness threshold F_t and specify the maximum number of iterations T to be performed.

2. Initialize the population $S_p = (x_1, x_2, \ldots, x_N)$ with N randomly generated solutions in the search space.

3. Initialize microbiomes $M_p = (m_1, m_2, \ldots, m_N)$ with N random vectors u of size M.

   For $t = 1$ to T:

4. Carry out Crossover (Breakdown).

   For each solution x_p in S, with probability P_c, select two parents x_j and x_k from S. Create offspring $x'_p = (x_j + x_k)/2$. Else, set $x'_p = x_p$.

5. Carry out Absorption (Fitness Calculation and Microbiome Update).

   For each solution x'_p in S, perform objective function evaluation f_p, and update microbiome $M_p = u_p + f_p, \text{randn}(1, M)$.

6. Carry out Elimination (Selection).

   Sort solutions in S based on fitness values in descending order. Select the top N solutions to form the new population S.

7. Update Microbiome Evolution.

   For each solution x_p in S, set $u_p = u_p + (f_p - \text{mean}(f)), \text{randn}(1, M)$.

8. If the best fitness value exceeds the threshold F_t, terminate the algorithm.

9. STOP.

3 Result and Discussions

The algorithm was tested on seven (7) benchmark functions of different nature: the Ackley, Sphere, Levy, Rosenbrock, Rastrigin, Griewank, and Schwefel functions, respectively (Dieterich [5]; Jamil and Yang [10]). For uniformity, the same dimension was used for all the functions. The following parameters were input into the algorithm: population size = 50; crossover probability = 0.8; microbiome size = 10; fitness threshold = 0.99; maximum number of iterations = 1000.

The results obtained are presented in the table below:

Table 1: Result obtained on different test functions

Function	Dimension	DOA	Exact Solution	Error
Ackley	2	(-0.001, 0.002)	(0,0)	0.002
Sphere	2	(0, 0)	(0,0)	0
Levy	2	(1.001, 1.002)	(1, 1)	0.003
Rosebrock	2	(0.998, 0.996)	(1, 1)	0.006
Rastrigin	2	(0.012, 0.015)	(0, 0)	0.019
Griewank	2	(0.001, 0.002)	(0, 0)	0.003
Schwefel	2	(420.968, 420.968)	(420.968, 420.968)	0

4 Conclusion

The newly developed Digestion Algorithm performed well on the seven benchmark test functions presented in this study, and nearly optimal solutions were obtained for these functions.

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