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Spider-Tailed Horned Viper Optimization: An Effective Bio-Inspired Metaheuristic Algorithm for Solving Engineering Applications

Tareq Hamadneh[1] Belal Batiha[2] Osama Al-Baik[3] Zeinab Montazeri[4] Om Parkash Malik[5] Frank Werner[6] Gaurav Dhiman[7,8,9] Mohammad Dehghani[4]* Kei Eguchi[10]

[1]*Department of Mathematics, Al Zaytoonah University of Jordan, Amman 11733, Jordan*
[2]*Department of Mathematics, Faculty of Science and Information Technology, Jadara University, Irbid 21110, Jordan*
[3]*Department of Software Engineering, Princess Sumaya University for Technology, Amman, Jordan*
[4]*Department of Electrical and Electronics Engineering, Shiraz University of Technology, Shiraz 7155713876, Iran*
[5]*Department of Electrical and Software Engineering, University of Calgary, Calgary, AB T2N 1N4, Canada*
[6]*Faculty of Mathematics, Otto-von-Guericke University, P.O. Box 4120, 39016 Magdeburg, Germany*
[7]*Centre of Research Impact and Outcome, Chitkara University, Rajpura- 140417, Punjab, India*
[8]*Department of Computer Science and Engineering, Graphic Era Deemed to be University, Dehradun-248002, India*
[9]*Division of Research and Development, Lovely Professional University, Phagwara-144411, India*
[10]*Department of Information Electronics, Fukuoka Institute of Technology, Japan*
* Corresponding author's Email: adanbax@gmail.com

Abstract: This study presents a new optimization algorithm called Spider-Tailed Horned Viper Optimization (STHVO), inspired by the spider-tailed horned viper. The viper's unique hunting strategy, which involves using its spider-like tail to attract prey, serves as the basis for this algorithm. STHVO incorporates two key processes: exploration and exploitation. Exploration allows the algorithm to search broadly for potential solutions, similar to how the viper moves through varied terrains in search of prey. Exploitation refines these solutions, akin to the snake focusing on its target once it has been lured. STHVO was rigorously tested across twenty-three benchmark functions, including unimodal and multimodal test suites. These benchmarks provide a comprehensive framework for assessing the algorithm's performance. The results showed that STHVO effectively balances exploration and exploitation, consistently finding high-quality solutions and outperforming a dozen established metaheuristic algorithms on most benchmarks. The algorithm's superior performance in both theoretical and practical contexts highlights its robustness and versatility. Overall, STHVO offers a novel, nature-inspired approach to optimization, proving to be a powerful tool for achieving optimal solutions across diverse applications.

Keywords: Spider-tailed horned viper, Nature-inspired, Optimization, Metaheuristic, Optimization algorithm, Exploration, Exploitation.

1. Introduction

In various fields such as science, engineering, and industry, numerous problems present themselves with multiple potential solutions. These types of challenges are referred to as optimization problems. An optimization problem typically consists of three fundamental components: decision variables, constraints, and an objective function. The primary goal of optimization is to find the best possible solution from a set of feasible alternatives, effectively maximizing or minimizing the objective function under given constraints [1]. As science and technology have progressed, the complexity of optimization problems has increased significantly, leading to the emergence of highly intricate challenges. This complexity has necessitated the development of advanced tools and methodologies specifically designed to tackle these problems [2]. Broadly speaking, the approaches used to solve optimization problems can be classified into two major categories: deterministic methods and stochastic methods [3].

Deterministic methods have long been the traditional choice for solving optimization problems. These methods can be further subdivided into gradient-based techniques and non-gradient-based techniques. Gradient-based methods are particularly effective when dealing with optimization problems that are differentiable, linear, continuous, convex, and have low dimensionality [4]. However, as the complexity of optimization problems increases, these deterministic methods often lose their effectiveness, leading to suboptimal solutions as they become trapped in local optima [5, 6]. Real-world optimization problems are often characterized by complexities such as discrete and unknown search spaces, non-differentiable and non-linear nature, discontinuities, non-convexity, and high dimensionality [7]. The inherent limitations of deterministic methods in handling such complex problems have motivated researchers to explore and develop alternative strategies [8, 9]. This has led to the rise of stochastic approaches, which are designed to better navigate the intricate landscapes of real-world optimization problems [10].

Stochastic methods differ fundamentally from deterministic ones in that they do not rely on gradient information from the objective function or constraints. Instead, these methods employ random searches across the problem-solving space, using trial-and-error processes combined with stochastic operators to identify suitable solutions. Among the most popular stochastic approaches are metaheuristic algorithms, which are designed to mimic the collective intelligence observed in natural systems, such as animal groups, insect colonies, and social behaviors [11].

Metaheuristic algorithms generally start the optimization process by generating an initial set of random solutions within the search space. These solutions are then iteratively improved through various algorithm-specific mechanisms. During each iteration, the algorithm seeks to refine its understanding of the search space by updating and retaining the best solution identified so far. The process continues until the algorithm converges to a final solution, which is proposed as the best possible answer to the problem. However, due to the inherent randomness of the search process, there is no guarantee that the solution obtained will precisely match the global optimum. As a result, the solutions generated by metaheuristic algorithms are often referred to as quasi-optimal solutions—solutions that are near the global optimum but not necessarily the absolute best [12]. When comparing the performance of different metaheuristic algorithms on a given optimization problem, the algorithm that converges most effectively to a quasi-optimal solution close to the global optimum is generally considered to be the superior method. For a metaheuristic algorithm to be effective, it must perform well on both a global and local scale. Global search, which represents the exploration capability of the algorithm, allows it to scan diverse regions of the search space to identify the area containing the global optimum. This helps the algorithm avoid becoming trapped in local optima. Local search, on the other hand, represents the exploitation capability of the algorithm. It focuses on refining the search within promising regions of the space, leading to better solutions that are closer to the global optimum. Since exploration and exploitation are conflicting objectives, a successful metaheuristic algorithm must strike an optimal balance between these two processes to conduct an effective search [13].

The continuous pursuit of more effective optimization solutions has driven researchers to design a multitude of metaheuristic algorithms. These algorithms draw inspiration from a wide range of sources, including natural phenomena, animal behavior, physical laws, biological processes, human social interactions, and even games. For instance, the Genetic Algorithm (GA) [14] is based on concepts from biology and genetics, while Particle Swarm Optimization (PSO)[15] is inspired by the movement patterns of birds and fish. The Spring Search Algorithm (SSA) [16] draws from Hooke's law and the tensile force of springs, whereas Teaching Learning Based Optimization (TLBO) [17] is modeled after the dynamics between teachers and students in a classroom setting. Additionally, the Darts Game Optimizer (DGO) [18] is inspired by the strategic approach players use to score points in the game of darts.

The primary research question explored in this study is whether the development of new metaheuristic algorithms remains necessary, considering the vast array of existing ones. The No Free Lunch (NFL) theorem [19] offers a significant viewpoint on this matter. It posits that the effectiveness of a specific metaheuristic algorithm in addressing a certain set of optimization problems does not inherently translate to success in solving different types of problems. According to the NFL theorem, it is impossible to predict in advance how well a metaheuristic algorithm will perform on a new optimization problem. As a result, no single algorithm can be universally regarded as the best across all optimization contexts. This perspective reinforces the idea that the search for new metaheuristic algorithms is not only justified but essential. The ongoing development of new algorithms is crucial for discovering more efficient and effective solutions to the diverse and complex optimization problems that arise in various fields. The limitations imposed by the NFL theorem highlight the need for continued innovation in algorithm design, as each new algorithm may bring unique strengths that make it particularly well-suited for specific types of problems. Drawing inspiration from the NFL theorem, the authors of this paper have undertaken the task of developing a new metaheuristic algorithm. This algorithm aims to address some of the existing challenges in optimization and to contribute to the broader landscape of problem-solving tools by offering a fresh approach that could excel where others might fall short.

The novelty and significant contribution of this paper lie in the introduction of a new swarm-based metaheuristic algorithm called Spider-Tailed Horned Viper Optimization (STHVO). This algorithm is specifically designed to tackle optimization tasks by drawing inspiration from the natural behaviors of the spider-tailed horned viper—a unique reptile known for its distinctive hunting strategy.

The key scientific contributions of this research are as follows:

- STHVO is designed based on simulation of the natural behaviors of spider-tailed horned viper in the wild.
- The fundamental inspiration in the design of STHVO is the hunting strategy of spider-tailed horned vipers in two stages of moving towards suitable ambushes and seducing the prey through the spider tail.
- STHVO is mathematically modeled based on the simulation of the hunting strategy of spider-tailed horned vipers in two phases of exploration and exploitation.
- The performance of STHVO for solving optimization problems is tested on twenty-three standard benchmark functions, including unimodal and multimodal test suite.
- The performance of STHVO for solving optimization problems is compared with the performance of twelve well-known metaheuristic algorithms.

The remainder of this paper is structured as follows: Section 2 introduces and models the proposed STHVO approach. Section 3 presents the simulation studies and results. Finally, Section 4 concludes the paper and offers suggestions for future research directions.

2. Spider-tailed horned viper optimization

This section provides an in-depth explanation of the theoretical foundation behind the proposed Spider-Tailed Horned Viper Optimization (STHVO) algorithm. Following this, the algorithm is mathematically modeled to facilitate its application in solving a wide range of optimization problems.

2.1 Inspiration of STHVO

The spider-tailed horned viper (Pseudocerastes urarachnoides) is a species of venomous viper, in the family Viperidae and genus Pseudocerastes [20]. The habitat of this viper is in the west of Iran near the border area with Iraq. The spider-tailed horned viper has a unique tail that resembles a spider. It uses this tail to lure and attract insectivorous birds. The head of the spider-tailed horned viper has two protrusions above the eyes that look similar to horns [21]. The spider-tailed horned viper has a deceptive strategy during hunting to trap birds and insects. They first go to suitable hunting areas where they can ambush well. Then, the spider-tailed horned viper hides itself and puts its tail under the soil so that only the spider-shaped part of the tail is visible. With this strategy, other animals will only notice the spider-tailed horned viper's tail without seeing it. These deceived animals approach the tail of the spider-tailed horned viper with the greed of hunting spiders. At this moment, the spider-tailed horned viper attacks and hunts the deceived animal in a very fast reaction and leap that does not take even a second. A video clip of the hunting strategy of the spider-tailed horned viper is published by Fathinia et al at http://dx.doi.org/10.6084/m9.figshare.1454446 [22].

Among the natural behaviors observed of the spider-tailed horned viper in the wild, the hunting strategy of this animal is very significant. This strategy has two main steps (i) moving towards the hunting ambush areas and (ii) luring the prey through the spider tail. Modeling these prominent behaviors in spider-tailed horned vipers has been the key inspiration in the proposed STHVO design.

2.2 Algorithm initialization

The newly introduced Spider-Tailed Horned Viper Optimization (STHVO) algorithm is a population-based technique where each member of the population is represented by a spider-tailed horned viper. In this framework, each viper identifies values for the decision variables according to its specific position within the search space. Consequently, within the STHVO algorithm, every spider-tailed horned viper symbolizes a potential solution to the optimization problem at hand. Mathematically, this can be depicted as a vector, with each element of the vector corresponding to a specific dimension of the viper's position. These elements reflect the values of the problem's variables.

At the start of the STHVO process, the positions of all spider-tailed horned vipers within the search space are initialized randomly, following a specific equation or rule as defined in Eq. (1). This initial random placement allows the algorithm to explore a diverse range of possible solutions, setting the stage for the subsequent optimization process.

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \quad (1)$$

Here X_i is the i'th spider-tailed horned viper (i.e., candidate solution), $x_{i,j}$ is the its j'th dimension (i.e., decision variable), N is the number of spider-tailed horned vipers, m is the number of decision variables, r is a random number in the interval $[0-1]$, lb_j is a lower bound, and ub_j is an upper bound on the j'th decision variable.

In the STHVO algorithm, the spider-tailed horned vipers collectively constitute the population. From a mathematical perspective, this population can be represented as a collection of vectors. These individual vectors, which describe the position of each viper within the search space, can be aggregated and modeled using a matrix, as outlined in Eq. (2). This matrix encapsulates the entire population, with each row corresponding to a single spider-tailed horned viper and each column representing a specific dimension of the search space or a decision variable.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} \cdots x_{1,d} \cdots x_{1,m} \\ \vdots \ \ddots \ \vdots \ \iddots \ \vdots \\ x_{i,1} \cdots x_{i,d} \cdots x_{i,m} \\ \vdots \ \iddots \ \vdots \ \ddots \ \vdots \\ x_{N,1} \cdots x_{N,d} \cdots x_{N,m} \end{bmatrix}_{N\times m} \quad (2)$$

Here X is the population matrix of STHVO.

Corresponding to each spider-tailed horned viper as a candidate solution for the variables of the problem, N values for the objective function can be evaluated. These calculated values provide insight into how well each candidate solution performs in relation to the objective. Mathematically, these objective function values for the entire population can be organized and represented as a vector, as shown in Eq. (3). This vector captures the performance of each spider-tailed horned viper, with each element corresponding to the objective function value of a specific viper within the population.

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \quad (3)$$

Here F is the objective function values vector and F_i is the objective function value obtained from the i'th spider-tailed horned viper.

Within the population of spider-tailed horned vipers, the individual that yields the most favorable value for the objective function is identified as the optimal or best member. Since both the positions of the vipers in the search space and their corresponding objective function values are updated during each iteration, it is crucial to also update the identification of the best member accordingly.

In the design of the Spider-Tailed Horned Viper Optimization (STHVO) algorithm, the process of updating the positions of population members in each iteration is guided by the natural hunting behavior of spider-tailed horned vipers. This behavior is modeled and incorporated into the algorithm through two distinct phases, which are elaborated upon in the following sections. These phases are designed to enhance the search process, enabling the algorithm to effectively explore and exploit the search space in order to find the optimal solution.

2.3 Phase 1: Moving to suitable locations to ambush for hunting (Exploration phase)

The spider-tailed horned viper uses camouflage and ambush strategy for hunting. This animal has the ability to move to positions that have suitable conditions for camouflage. This strategy leads the spider-tailed horned viper to move to different areas in order to discover a suitable ambush. This natural behavior of the spider-tailed horned viper is similar to the concept of exploration in the global search to identify the original optimal region in metaheuristic algorithms. Therefore, the mathematical modeling of the spider-tailed horned viper's movement towards the appropriate ambush, creates the ability of discovery in the design of STHVO. In the STHVO design, for each spider-tailed horned viper, the position of other spider-tailed horned vipers that have a better value for the objective function are assumed as candidate positions for ambushes. Therefore, the set of candidate ambushes for each spider-tailed horned viper is specified using Eq. (4).

$$CA_i = \{X_k | F_k \leq F_i\} \quad (4)$$

Here CA_i is the set of candidate ambushes for the ith spider-tailed horned viper and X_k is the kth population members which has a better objective function value (F_k) compared to the objective function value of the ith population member (F_i).

Among these candidate positions for ambush, one position is randomly selected as the ambush for hunting. Based on the modeling of the spider-tailed horned viper's movement towards the selected ambush for hunting, a new proposed location for the corresponding spider-tailed horned viper is calculated using Eq. (5). Then, according to Eq. (6), this new location, if it improves the value of the objective function, replaces the previous location of the corresponding spider-tailed horned viper.

$$x_{i,j}^{P1} = x_{i,j} + \sin\left(\frac{\pi}{2}r\right).\left(SA_{i,j} - I \,.\, x_{i,j}\right) \quad (5)$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} < F_i \\ X_i, & else \end{cases} \quad (6)$$

Here X_i^{P1} is the new location proposed for the ith spider-tailed horned viper based on the first phase of STHVO, $x_{i,j}^{P1}$ is its jth dimension, F_i^{P1} is its objective function value, r is a random number in the interval $[0-1]$, SA_i is the location of the selected ambush for the ith spider-tailed horned viper, $SA_{i,j}$ is its jth dimension, and I is a random number which selected from set $\{1,2\}$.

2.4 Phase 2: Attracting and attacking the prey through caudal luring strategy (Exploitation phase)

The most obvious characteristic of the spider-tailed horned viper is its unique tail, which is very similar to a spider. spider-tailed horned viper uses this feature to deceive its prey. In this strategy, the spider-tailed horned viper camouflages its body in ambush positions for hunting. Then it hides its tail in such a way that only the spider-shaped part is exposed. Then, in order to lure prey, it shakes the spider-shaped part of its tail alternately. Birds and insects in that location only see the spider-shaped tail and approach the spider-tailed horned viper in order to hunt the spider. At this time, the spider-tailed horned viper attacks and hunts the prey with high action speed. This happens near the location where the spider-tailed horned viper is lurking and leads to a small movement of this animal in that position. This small change in the ambush area is similar to the concept of exploitation in local search to achieve better solutions in metaheuristic algorithms. In order to model this STHVO phase, a random location near each spider-tailed horned viper is calculated using Eq. (7). Then, if the value of the objective function is improved, the position of the spider-tailed horned viper is updated to this new position according to Eq. (8).

$$x_{i,j}^{P2} = x_{i,j} + \left(1 - 2\,.\,\sin\left(\frac{\pi}{2}r\right)\right)\frac{\left(ub_j - lb_j\right)}{t} \quad (7)$$

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} < F_i \\ X_i, & else \end{cases} \quad (8)$$

Here X_i^{P2} is the new location proposed for the ith spider-tailed horned viper based on the second phase of STHVO, $x_{i,j}^{P2}$ is its jth dimension, F_i^{P2} is its objective function value, r is a random number in the interval $[0-1]$, and t is the iteration counter.

3. Simulation studies

In this section, we present a series of simulation studies conducted to evaluate the effectiveness of the proposed STHVO approach in solving optimization problems. To achieve this, the performance of the Spider-Tailed Horned Viper Optimization (STHVO) algorithm has been rigorously tested against a set of sixty-eight standard benchmark functions. These benchmark functions include unimodal, high-dimensional multimodal, and fixed-dimensional multimodal functions [23]. The STHVO's optimization capabilities have been compared against twelve well-established metaheuristic algorithms, namely GA [14], PSO [24], GSA [25], TLBO [17], MVO [26], GWO [27], WOA [28], MPA [29], TSA [30], RSA [31], AVOA [32], and WSO [33].

To ensure a robust comparison, the STHVO and each of the competitor algorithms were executed twenty independent times for each benchmark function, with each run consisting of 1000 iterations. The performance outcomes from these simulations are summarized using six key indicators: mean, best, worst, standard deviation (std), median, and rank. The "mean" value of each indicator serves as the primary criterion for ranking the overall performance

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of the metaheuristic algorithms, providing a comprehensive measure of their optimization efficiency across the tested functions.

3.1 Evaluation for unimodal benchmark

To evaluate the performance of optimization algorithms in solving unimodal optimization problems, seven benchmark functions, denoted as F1 through F7, have been selected. These functions are characterized by the absence of local optima, making them particularly suitable for assessing the exploitation capabilities of metaheuristic algorithms. Table 1 presents the optimization results for these unimodal functions using the Spider-Tailed Horned Viper Optimization (STHVO) algorithm and the competing algorithms.

The simulation results indicate that STHVO demonstrates exceptional exploitation abilities, achieving the global optimum for functions F1, F2, F3, F4, and F6. Notably, STHVO emerges as the top-performing optimizer for the F7 function as well. For function F5, STHVO ranks as the second-best optimizer, closely following the African Vultures Optimization Algorithm (AVOA).

Overall, the analysis of these results highlights STHVO's superior performance in solving unimodal functions, particularly in terms of local search and exploitation efficiency. This makes STHVO a significantly more effective optimizer compared to the other algorithms tested.

Table 1. Optimization results of unimodal test functions

F		STHVO	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
F1	mean	0	149.52885	0	0	1.19E-49	5.68E-47	1.23E-149	0.1299222	1.02E-58	8.51E-75	1.01E-16	0.2247862	34.259744
	best	0	10.970151	0	0	3.10E-52	2.17E-51	1.38E-171	0.0810732	4.42E-61	7.19E-77	6.30E-17	4.68E-05	16.490891
	worst	0	763.40843	0	0	7.25E-49	7.89E-46	2.45E-148	0.2053109	7.50E-58	5.24E-74	1.59E-16	4.150064	70.225154
	std	0	192.04337	0	0	2.12E-49	1.80E-46	5.49E-149	0.0316133	1.93E-58	1.52E-74	2.84E-17	0.9242966	13.521229
	median	0	67.918469	0	0	2.12E-50	2.03E-48	1.85E-159	0.1238226	1.34E-59	1.72E-75	9.28E-17	0.0061152	31.283032
	rank	1	11	1	1	5	6	2	8	4	3	7	9	10
F2	mean	0	1.9334906	1.22E-261	0	8.38E-28	1.33E-28	5.32E-101	0.2406114	9.59E-35	8.96E-39	5.10E-08	0.7892474	3.1294029
	best	0	0.5276386	0	0	1.29E-29	2.64E-30	2.57E-112	0.160513	7.89E-36	3.41E-40	3.62E-08	0.0659251	1.925071
	worst	0	6.4384296	2.45E-260	0	4.62E-27	8.83E-28	1.06E-99	0.3998012	3.82E-34	4.84E-38	6.81E-08	2.45481	4.6047706
	std	0	1.4412668	0	0	1.19E-27	2.49E-28	2.38E-100	0.060872	9.06E-35	1.16E-38	9.78E-09	0.63236	0.6912539
	median	0	1.4588353	1.96E-283	0	2.36E-28	2.43E-29	4.97E-108	0.2185072	7.80E-35	5.35E-39	4.98E-08	0.5121005	2.8793431
	rank	1	11	2	1	7	6	3	9	5	4	8	10	12
F3	mean	0	1459.0408	0	0	4.31E-13	4.01E-08	21269.937	13.637584	5.49E-15	5.21E-25	466.52051	233.04072	2151.6372
	best	0	489.21634	0	0	2.45E-26	3.28E-21	1007.8992	7.3987313	2.15E-19	3.02E-28	225.44725	70.038065	1419.3192
	worst	0	2979.8443	0	0	5.44E-12	6.51E-07	48145.225	31.198209	4.53E-14	8.16E-24	696.68112	535.58465	3269.1486
	std	0	580.77002	0	0	1.24E-12	1.47E-07	10197.364	5.7430243	1.13E-14	1.81E-24	148.76645	148.45344	506.86522
	median	0	1549.3879	0	0	7.00E-15	1.13E-13	20800.105	12.710615	3.54E-16	1.08E-26	478.81643	196.91865	2084.9781
	rank	1	9	1	1	4	5	11	6	3	2	8	7	10
F4	mean	0	17.541482	9.37E-264	0	2.98E-19	0.0046062	42.358551	0.4972783	8.97E-15	2.27E-30	0.9665494	6.2633539	3.0015409
	best	0	10.603217	0	0	2.71E-20	2.16E-05	0.2259775	0.2870264	5.52E-16	1.32E-31	1.385E-08	3.5220248	1.9786598
	worst	0	27.655403	1.3E-262	0	2.18E-18	0.016076	90.467984	0.8355712	1.86E-14	9.13E-30	3.2669704	12.371081	3.6417756
	std	0	3.2042694	0	0	4.79E-19	0.0056337	33.451351	0.1344543	5.58E-15	2.62E-30	1.0824739	2.4730637	0.4579349
	median	0	17.499133	2.98E-284	0	1.19E-19	0.0016009	41.31905	0.4796231	9.79E-15	9.27E-31	0.491248	5.3459192	3.0950185
	rank	1	11	2	1	4	6	12	7	5	3	8	10	9
F5	mean	0.1971011	10733.849	1.167E-05	11.581195	23.433788	28.137151	27.152241	315.97201	26.827402	26.828334	41.224414	221.95213	487.96403
	best	0.0032627	1239.1579	1.581E-06	8.33E-29	22.233935	26.150697	26.463012	29.104389	26.048089	25.639963	25.965259	21.266982	284.94753
	worst	0.8194701	72445.385	6.94E-05	28.990119	24.299103	28.892032	28.719453	2049.1037	27.948366	28.753332	325.61607	3263.9422	817.17888
	std	0.215288	16805.071	1.634E-05	14.552556	0.4862913	1.0719239	0.6010416	560.52109	0.6425883	0.8249373	66.939143	716.99517	125.64149
	median	0.1116387	4929.9802	5.021E-06	1.07E-28	23.374827	28.832572	27.007881	51.634883	27.073941	26.460319	26.208759	57.655514	478.50447
	rank	2	13	1	3	4	8	7	11	5	6	9	10	12
F6	mean	0	140.60052	6.07E-08	6.6165029	1.71E-09	3.631487	0.0677189	0.1585581	0.6379952	1.2772201	1.08E-16	0.0537603	34.190471
	best	0	12.027894	5.48E-09	4.3714174	7.73E-10	2.7998407	0.0100785	0.082866	2.45E-01	0.6522531	5.04E-17	1.06E-05	16.294547
	worst	0	510.99473	1.637E-07	7.4374317	4.62E-09	4.789133	0.2700998	0.2296629	1.0085348	2.1866556	4.35E-16	0.7291825	52.265465
	std	0	169.22068	4.426E-08	1.1109393	8.90E-10	0.6506473	0.0770929	0.0420361	0.275652	0.4875699	8.76E-17	0.1620834	8.6007769
	median	0	46.185433	4.696E-08	7.25	1.54E-09	3.5600403	0.0358689	0.1509461	0.7488091	1.2537722	8.12E-17	0.004526	35.932867
	rank	1	13	4	11	3	10	6	7	8	9	2	5	12
F7	mean	2.38E-06	0.022533	0.022536	0.022504	0.022953	0.026143	0.02367	0.031097	0.02327	0.023487	0.066601	0.17512	0.03167
	best	1.74E-07	0.006973	0.006978	0.006948	0.007164	0.009358	0.007369	0.014017	0.00723	0.007765	0.044391	0.054068	0.020538
	worst	7.52E-06	0.040502	0.04044	0.04041	0.040846	0.044866	0.041255	0.045884	0.040922	0.041686	0.097328	0.314771	0.045561
	std	2.15E-06	0.008834	0.00881	0.008809	0.008834	0.008798	0.009182	0.00968	0.008943	0.008942	0.016455	0.068725	0.007975
	median	1.63E-06	0.023537	0.023519	0.023482	0.023802	0.02786	0.023754	0.032652	0.024449	0.024472	0.063053	0.182945	0.033758
	rank	1	3	4	2	5	9	8	10	6	7	12	13	11
Sum rank		8	71	15	20	32	50	49	58	36	34	54	64	76
Mean rank		1.1428571	10.142857	2.1428571	2.8571429	4.57	7.1428571	7	8.2857143	5.1	4.8571429	7.71	9.14	10.857143
Total ranking		1	12	2	3	4	8	7	10	6	5	9	11	13

3.2 Evaluation for high-dimensional multimodal benchmark

To assess the effectiveness of metaheuristic algorithms in tackling high-dimensional multimodal optimization problems, six benchmark functions, labeled F8 through F13, have been chosen. These functions are characterized by a substantial number of local optima, making them ideal for evaluating the exploration capabilities of metaheuristic algorithms, particularly in their ability to perform global searches and avoid entrapment in local optima.

The results of applying the Spider-Tailed Horned Viper Optimization (STHVO) algorithm, along with other competing algorithms, to these functions are summarized in Table 2. The simulation outcomes reveal that STHVO successfully converged to the global optimum for functions F9 and F11, demonstrating robust exploration capabilities. Furthermore, STHVO outperformed all other algorithms for functions F8, F10, F12, and F13, establishing itself as the best optimizer for these problems. When comparing the simulation results, it becomes evident that STHVO excels in identifying optimal regions within the search space. Its high exploration ability has consistently provided superior performance in solving the high-dimensional multimodal optimization problems represented by functions F8 through F13, outperforming the other metaheuristic algorithms under comparison.

3.3 Evaluation for fixed-dimensional multimodal benchmark

To evaluate the performance of metaheuristic algorithms in solving fixed-dimensional multimodal optimization problems, ten benchmark functions, designated as F14 through F23, were selected. These functions are characterized by a limited number of local optima, making them ideal for simultaneously assessing the exploration and exploitation capabilities of metaheuristic algorithms, as well as their ability to maintain a balance between these two aspects during the search process.

The outcomes of implementing the Spider-Tailed Horned Viper Optimization (STHVO) algorithm, along with other competing algorithms, on these functions are documented in Table 3.

Table 2. Optimization results of high-dimensional multimodal test functions

F		STHVO	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
F8	mean	-12563.1	-7377.4	-11771.4	-6061.5	-9568.98	-6587.66	-9749.32	-8134.48	-6630.9	-5995.36	-3783.74	-7021.35	-8428.39
	best	-12569.5	-9117.48	-11996.7	-6261.8	-10137.6	-7450.95	-11907.7	-8965.49	-7565.68	-7379.13	-4427.23	-8105.31	-9446.08
	worst	-12447.1	-6085.2	-11134.6	-5761.79	-8745.39	-5618.68	-7811.64	-7254.01	-5851.95	-5302.91	-3273.81	-5933.15	-7210.39
	std	29.58355	844.5751	225.3039	148.21	397.2406	512.338	1580.941	476.9387	480.7458	539.692	398.2497	593.2177	730.3683
	median	-12569.5	-7302.33	-11839.6	-6095.49	-9591.89	-6493.06	-9217.87	-8100.31	-6623.39	-5954.03	-3648.61	-6993.77	-8500.88
	rank	1	7	2	11	4	10	3	6	9	12	13	8	5
F9	mean	0	28.97533	6.583454	6.583454	6.583454	148.3763	6.583454	86.63614	6.816212	6.583454	26.79648	51.30779	54.16262
	best	0	19.64655	2.40439	2.40439	2.40439	78.41589	2.40439	53.82452	2.40439	2.40439	15.81141	18.73848	30.7041
	worst	0	54.36277	10.46883	10.46883	10.46883	234.1906	10.46883	168.1096	10.66632	10.46883	36.61418	81.58823	81.3586
	std	0	9.48664	2.267385	2.267385	2.267385	35.88933	2.267385	28.47394	2.466234	2.267385	5.999449	17.67074	15.78162
	median	0	26.10366	6.251354	6.251354	6.251354	141.5104	6.251354	83.45882	6.380382	6.251354	26.78886	48.71958	48.87199
	rank	1	6	2	2	2	10	3	9	4	2	5	7	8
F10	mean	8.88E-16	4.715424	0.379716	0.379716	0.379716	1.591003	0.379716	0.87383	0.379716	0.379716	0.379716	2.959294	3.381532
	best	8.88E-16	3.236274	0.229553	0.229553	0.229553	0.256334	0.229553	0.322181	0.229553	0.229553	0.229553	1.78901	2.852752
	worst	8.88E-16	6.178225	0.661322	0.661322	0.661322	3.146229	0.661322	1.903958	0.661322	0.661322	0.661322	5.153978	3.999378
	std	0	0.868365	0.110813	0.110813	0.110813	1.370093	0.110813	0.544498	0.110813	0.110813	0.110813	0.863615	0.356114
	median	8.88E-16	4.631668	0.37759	0.37759	0.37759	1.135053	0.37759	0.675923	0.37759	0.37759	0.37759	2.942725	3.341623
	rank	1	12	2	2	4	9	3	8	6	5	7	10	11
F11	mean	0	1.785179	0.007343	0.007343	0.007343	0.010377	0.014797	0.309377	0.010756	0.007343	6.371139	0.057229	1.231349
	best	0	0.957958	0.000986	0.000986	0.000986	0.001249	0.000986	0.192811	0.000986	0.000986	2.151214	0.007684	1.006126
	worst	0	4.249801	0.027298	0.027298	0.027298	0.031765	0.093317	0.495266	0.056482	0.027298	9.179713	0.212743	1.506171
	std	0	1.013796	0.006833	0.006833	0.006833	0.009303	0.026034	0.075302	0.013786	0.006833	2.191466	0.053252	0.143782
	median	0	1.43147	0.004538	0.004538	0.004538	0.008055	0.004538	0.316213	0.006388	0.004538	6.259994	0.035366	1.220211
	rank	1	9	2	2	2	3	5	7	4	2	10	6	8
F12	mean	2.63E-33	3.690078	0.180708	1.24209	0.180708	6.087865	0.186231	1.030065	0.212709	0.253438	0.310974	1.40834	0.322773
	best	2.13E-34	0.260998	4.62E-06	0.612509	4.62E-06	0.608211	0.000629	0.00134	0.011042	0.070265	0.000291	3.6E-05	0.044619
	worst	5.73E-33	8.84428	0.524574	1.717751	0.524574	10.14883	0.53572	3.301456	0.561	0.589744	0.681288	4.088235	0.563235
	std	1.7E-33	2.48161	0.186318	0.341333	0.186318	3.164144	0.186489	1.126013	0.184812	0.18446	0.24958	1.452063	0.167862
	median	2.62E-33	3.234149	0.14931	1.28368	0.14931	5.844715	0.153759	0.470796	0.179609	0.215524	0.302502	1.163642	0.313081
	rank	1	12	3	10	2	13	4	9	5	6	7	11	8
F13	mean	6.7E-32	818.9346	0.694804	0.694804	0.696755	3.235295	0.879948	0.719281	1.123419	1.555968	0.695667	5.414915	2.712071
	best	1.14E-34	16.8689	0.016641	0.016641	0.016641	2.247812	0.142551	0.026029	0.277828	0.619216	0.016721	0.129691	1.222117
	worst	4.34E-31	14676.65	2.848373	2.848373	2.848373	5.032679	3.141911	2.872739	3.285848	3.672998	2.848373	22.19864	5.383347
	std	1.3E-31	3537.918	0.753893	0.753893	0.752989	0.762291	0.83508	0.758286	0.711732	0.777076	0.752947	5.875425	1.033713
	median	3.38E-32	30.15666	0.459162	0.459162	0.459162	3.142976	0.671471	0.480768	0.951963	1.428021	0.459162	3.578458	2.57838
	rank	1	13	3	2	5	11	7	6	8	9	4	12	10
Sum Rank		6	59	14	29	19	56	25	45	36	36	46	54	50
Mean rank		1	9.833333	2.333333	4.833333	3.166667	9.333333	4.166667	7.5	6	6	7.666667	9	8.333333
Total ranking		1	12	2	5	3	11	4	7	6	6	8	10	9

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Table 3. Optimization results of fixed-dimensional multimodal test functions

F		STHVO	WSO	AVOA	RSA	MPA	TSA	WOA	MVO	GWO	TLBO	GSA	PSO	GA
F14	mean	0.998004	2.159387	2.406607	3.653747	2.159387	5.700948	2.71583	2.159387	3.312029	2.201135	2.867583	3.479798	2.159797
	best	0.998004	1.008449	1.008449	1.033767	1.008449	1.342461	1.008449	1.008449	1.174451	1.008449	1.198144	1.008449	1.008449
	worst	0.998004	4.719846	5.624475	9.631941	4.719846	9.631941	5.451903	4.719846	6.802766	4.897857	7.206773	8.974989	4.720026
	std	7.8E-17	1.142957	1.380167	2.705568	1.142957	2.822338	1.445938	1.142957	1.872511	1.242294	1.668326	2.777701	1.14279
	median	0.998004	1.859308	2.187961	2.69427	1.859308	6.427128	2.36768	1.859308	2.862881	1.859309	2.542571	2.900702	1.862184
	rank	1	2	6	11	2	12	7	3	9	5	8	10	4
F15	mean	0.000307	0.002682	0.002635	0.002955	0.002798	0.006434	0.002763	0.00362	0.00394	0.00398	0.003328	0.004021	0.006533
	best	0.000307	0.000612	0.000612	0.00084	0.000683	0.000675	0.000678	0.000695	0.000675	0.000676	0.001261	0.000612	0.000888
	worst	0.000307	0.007582	0.007582	0.007759	0.007583	0.028048	0.007776	0.013063	0.016022	0.00936	0.008411	0.016022	0.020864
	std	2.2E-19	0.002332	0.002329	0.002335	0.002337	0.006782	0.002311	0.003608	0.004247	0.00325	0.002412	0.004996	0.006693
	median	0.000307	0.001513	0.001521	0.001949	0.001695	0.004944	0.001744	0.002016	0.002436	0.003598	0.002149	0.001808	0.003625
	rank	1	3	2	6	5	12	4	8	9	10	7	11	13
F16	mean	-1.03163	-1.03146	-1.03146	-1.03106	-1.03146	-1.0308	-1.03146	-1.03146	-1.03146	-1.03146	-1.03146	-1.03146	-1.03146
	best	-1.03163	-1.03162	-1.03162	-1.03161	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162
	worst	-1.03163	-1.03096	-1.03096	-1.02934	-1.03096	-1.01818	-1.03096	-1.03096	-1.03096	-1.03096	-1.03096	-1.03096	-1.03096
	std	2.27E-16	0.000219	0.000219	0.000751	0.000219	0.003224	0.000219	0.000219	0.000219	0.000219	0.000219	0.000219	0.000218
	median	-1.03163	-1.03156	-1.03156	-1.03139	-1.03156	-1.03156	-1.03156	-1.03156	-1.03156	-1.03156	-1.03156	-1.03156	-1.03156
	rank	1	6	2	9	2	10	3	5	4	7	2	2	8
F17	mean	0.397887	0.483259	0.483259	0.485208	0.483259	0.483276	0.48326	0.483259	0.48326	0.484446	0.483259	0.568651	0.60286
	best	0.397887	0.397932	0.397932	0.398041	0.397932	0.397933	0.397932	0.397932	0.397932	0.397939	0.397932	0.397932	0.397933
	worst	0.397887	1.229545	1.229545	1.231145	1.229545	1.229547	1.229545	1.229545	1.229546	1.229608	1.229545	2.236707	2.236716
	std	0	0.225911	0.225911	0.225761	0.225911	0.225916	0.225911	0.225911	0.225911	0.225446	0.225911	0.495246	0.551718
	median	0.397887	0.398772	0.398772	0.400894	0.398772	0.398794	0.398772	0.398772	0.398772	0.399096	0.398772	0.398772	0.398794
	rank	1	2	2	8	2	6	5	3	4	7	2	9	10
F18	mean	3	3.475023	3.475023	3.475065	3.475023	7.451845	3.475056	3.475023	3.47503	3.475024	3.475023	3.475023	4.626432
	best	3	3	3	3.000001	3	3.000003	3.000001	3	3.000003	3.000002	3	3	3
	worst	3	7.752356	7.752356	7.752356	7.752356	37.08707	7.752381	7.752356	7.752367	7.752356	7.752356	7.752356	19.27203
	std	1.03E-15	1.580785	1.580785	1.580778	1.580785	11.38608	1.580777	1.580785	1.580786	1.580785	1.580785	1.580785	5.412602
	median	3	3.000178	3.000178	3.000218	3.000178	3.00037	3.000197	3.000178	3.000179	3.000178	3.000178	3.000178	3.000427
	rank	1	2	7	11	3	13	10	6	9	8	5	4	12
F19	mean	-3.86278	-3.85811	-3.85811	-3.84678	-3.85811	-3.85808	-3.85632	-3.85811	-3.85747	-3.85763	-3.85811	-3.85811	-3.8581
	best	-3.86278	-3.86273	-3.86273	-3.8626	-3.86273	-3.86269	-3.86189	-3.86273	-3.86272	-3.86256	-3.86273	-3.86273	-3.86273
	worst	-3.86278	-3.83572	-3.83572	-3.77012	-3.83572	-3.8357	-3.8356	-3.83572	-3.8324	-3.8327	-3.83572	-3.83572	-3.83571
	std	2.47E-15	0.006343	0.006343	0.021719	0.006343	0.006338	0.006134	0.006343	0.00711	0.007009	0.006343	0.006343	0.00634
	median	-3.86278	-3.85951	-3.85951	-3.85157	-3.85951	-3.85949	-3.85821	-3.85951	-3.85844	-3.85912	-3.85951	-3.85951	-3.85951
	rank	1	2	4	11	3	7	10	5	9	8	3	3	6
F20	mean	-3.322	-3.2118	-3.20676	-3.03288	-3.20178	-3.18491	-3.18305	-3.19172	-3.19388	-3.18908	-3.2193	-3.20429	-3.1718
	best	-3.322	-3.28077	-3.28077	-3.18515	-3.28077	-3.27951	-3.28065	-3.28005	-3.28077	-3.27681	-3.28077	-3.28077	-3.27648
	worst	-3.322	-2.96532	-2.91467	-2.17221	-2.91528	-2.96503	-2.89897	-2.96532	-2.96531	-2.885	-2.96532	-2.96532	-2.89383
	std	4.13E-16	0.084033	0.095229	0.246758	0.086886	0.094134	0.090991	0.080923	0.088149	0.092384	0.0788	0.088165	0.104907
	median	-3.322	-3.23189	-3.23137	-3.08281	-3.21493	-3.21473	-3.19135	-3.2134	-3.21839	-3.20534	-3.23398	-3.23137	-3.18421
	rank	1	3	4	13	6	10	11	8	7	9	2	5	12
F21	mean	-10.1532	-7.11438	-7.58704	-5.44167	-7.58704	-5.66557	-6.84071	-6.62876	-7.37421	-5.90874	-6.62382	-5.75059	-5.34852
	best	-10.1532	-9.20092	-9.20092	-7.05555	-9.20092	-8.25457	-9.20084	-8.27154	-9.2008	-8.16277	-8.27156	-9.20092	-9.03798
	worst	-10.1532	-3.51975	-6.60653	-4.46116	-6.60653	-3.46793	-4.46082	-3.49365	-4.53676	-4.36714	-3.46282	-3.44077	-3.32057
	std	2.61E-15	1.48715	0.747798	0.747797	0.747798	1.743831	1.455726	1.587257	1.106657	0.906905	1.555338	2.273289	1.818798
	median	-10.1532	-7.64768	-7.81093	-5.66555	-7.81093	-5.3662	-6.66618	-7.00334	-7.70119	-5.76634	-6.67918	-4.66721	-4.81568
	rank	1	5	2	12	3	11	6	7	4	9	8	10	13
F22	mean	-10.4029	-8.32128	-8.32128	-6.08448	-8.32128	-7.06477	-7.43175	-7.76466	-8.20923	-7.51985	-8.32128	-7.56724	-6.2662
	best	-10.4029	-9.33202	-9.33202	-7.09521	-9.33202	-9.24501	-9.04788	-9.332	-9.33182	-8.77075	-9.33202	-9.33202	-8.97291
	worst	-10.4029	-6.82732	-6.82732	-4.59051	-6.82732	-4.72904	-4.59051	-5.74068	-5.8747	-5.9162	-6.82732	-3.61345	-3.61071
	std	3.87E-15	0.721138	0.721138	0.721138	0.721138	1.527336	1.448649	1.367651	0.93333	0.81732	0.721138	2.052413	1.726511
	median	-10.4029	-8.21248	-8.21248	-5.97567	-8.21248	-6.97401	-8.0358	-8.11452	-8.21234	-7.50239	-8.21248	-8.21248	-6.42651
	rank	1	2	4	12	2	10	9	6	5	8	3	7	11
F23	mean	-10.5364	-7.40062	-8.21787	-5.93715	-8.21787	-6.77543	-7.10483	-7.87946	-8.21769	-7.30843	-7.96837	-6.78797	-6.30837
	best	-10.5364	-9.55581	-9.55581	-7.28001	-9.55581	-9.51657	-9.51225	-9.5558	-9.55562	-9.30909	-9.55581	-9.55581	-9.45463
	worst	-10.5364	-3.6095	-6.83425	-4.55845	-6.83425	-3.43119	-3.68769	-6.0108	-6.83407	-4.37991	-5.88916	-3.41939	-3.39234
	std	2.25E-15	1.819709	1.13996	1.140183	1.13996	1.991945	1.903664	1.203891	1.139953	1.409614	1.335705	2.832943	2.448788
	median	-10.5364	-7.493	-8.24264	-5.91768	-8.24264	-6.80198	-7.14983	-7.79849	-8.24239	-7.12691	-8.07751	-8.24264	-6.33748
	rank	1	7	3	13	2	11	9	6	4	8	5	10	12
Sum Rank		10	34	36	106	30	102	74	57	64	79	45	71	101
Mean rank		1	3.4	3.6	10.6	3	10.2	7.4	5.7	6.4	7.9	4.5	7.1	10.1
Total ranking		1	3	4	13	2	12	9	6	7	10	5	8	11

The simulation results indicate that STHVO emerged as the best optimizer for functions F15 and F21. For the remaining functions—F14, F16, F17, F18, F19, F20, F22, and F23—while STHVO exhibited comparable performance in terms of the "mean" index values with some of the competing algorithms, it demonstrated superior performance by achieving better results for the "standard deviation (std)" index. This suggests that STHVO not only delivers consistent results but also reduces variability in the outcomes, reflecting its robustness.

The analysis of these simulation results underscores that STHVO excels in maintaining a balance between exploration and exploitation throughout the optimization process. This balanced approach enables STHVO to deliver more effective performance in optimizing the fixed-dimensional multimodal functions F14 through F23 when compared to the other competing algorithms.

4. Conclusions and future works

In this paper, a new metaheuristic algorithm called Spider-Tailed Horned Viper Optimization (STHVO) was presented. The fundamental inspiration of SHTVO is the strategy of spider-tailed horned vipers during hunting in two stages (i) moving towards the hunting ambushes and (ii) luring the prey through the spider tail. STHOVO was mathematically modeled in two phases of exploration and exploitation in order to provide effective search at both global and local levels. The effectiveness of STHVO in solving optimization problems was tested on twenty-three benchmark functions of unimodal and multimodal test function. The optimization results of the benchmark functions showed that STHVO has a high success in exploration and exploitation, and balancing them during the optimization process. In order to analyze the ability of STHVO in optimization, the results obtained from the proposed approach were compared with the performance of twelve well-known metaheuristic algorithms. The analysis of the optimization results showed that STHVO has provided superior performance by providing better results in most of the benchmark functions compared to competitor algorithms.

The authors provide several study suggestions for further research, including the design of binary and multi-objective versions of STHVO. Employing STHVO in solving optimization problems in various sciences and real-world applications is another suggestion for further research.

Conflicts of Interest

"The authors declare no conflict of interest."

Author Contributions

Conceptualization, T.H, B.B, and O.A.B; methodology, TH, M.D, G.D, F.W, and K.E; software, K.E, O.P.M, B.B, G.D, and O.A.B; validation, K.E, M.D, F.W, and O.P.M; formal analysis, Z.M, M.D, K.E, and O.P.M; investigation, B.B, Z.M, and O.A.B; resources, T.H, Z.M, F.W, G.D, and B.B; data curation, K.E and O.A.B; writing—original draft preparation, M.D, T.H, F.W, and O.P.M; writing—review and editing, O.A.B, Z.M, B.B, G.D, and K.E; visualization, K.E; supervision, M.D; project administration, K.E, T.H, F.W, and O.P.M; funding acquisition, K.E.

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