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RESEARCH ARTICLE

Improving Golden Eagle Optimization Algorithm Through Using Wavelet Mutation

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ABSTRACT

The Golden Eagle Optimization (GEO) algorithm is another amazing nature inspired optimization algorithm based on the foraging behavior of the Golden Eagles. GEO is an excellent behavioral model of how Golden Eagles interact with one another while searching for prey, consisting of a population of virtual "eagles" that together represent potential solutions to the optimization problem. The "eagles" interact with one another and together communicate and move as a single unit towards something, in this case the optimal solution. In this paper, we expand upon this idea with a new version of the GEO algorithm, called Wavelet Mutation Golden Eagle Optimization (WMGEO). WMGEO introduces a wavelet mutation function into the GEO framework, which will allow the WMGEO algorithm to allow greater exploration and improved overall algorithm performance when solving difficult optimization problems. The WMGEO algorithm ultimately aims to resolve certain constraints exhibited in the GEO algorithm. WMGEO in particular aims to improve the quality of solution, speed of solution convergence, and stability of solution. A variety of benchmark test functions are used to evaluate the efficacy of the proposed method. The benchmark functions are divided into several categories, which provide a variety of challenges for WMGEO. These test functions fall into different types, which means these tests represent a comprehensive and diverse set of challenges for WMGEO. The results of the experiments show a strong impression of the algorithm. There are significant advancements regarding solution quality and convergence speed and consequently solution stability compared to the traditional GEO algorithm. This reinforces the promise and potential for WMGEO as an optimization technique illustrating greater efficacy than its predecessor across multiple options.

Keywords: Benchmark test function, Golden eagle optimization, Nature-inspired, Standard deviation, Wavelet mutation

Introduction

Optimization strategies derived from nature like social insects, biological organisms, and physical systems utilize computational techniques to resolve multifaceted optimization issues.[1] Nature-inspired algorithms harness the ideas of reproduction, mutation, and natural selection to progressively improve a given population of potential solutions to reach optimal or satisfactory results.[2,3] Such algorithms can solve issues with non-linear complexity which traditional algorithms find difficult, thus proving effective in the fields of engineering, biology, and economics.[4,5] The synthesis of computational techniques with natural paradigms has led to a diverse range of algorithms, each tailored to specific problem domains. Nature-inspired optimization algorithms contribute significantly to scientific advancements and practical applications by providing innovative and powerful solutions to real-world optimization problems.[6,7]

Nature-inspired optimization algorithms possess a notable advantage in their inherent suitability for parallelization and scalability, enabling them to handle computationally intensive and large-scale optimization tasks.[8] This characteristic makes them

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versatile across various domains and facilitates integration into high-performance computing environments, making them indispensable tools for addressing real-world complexities. Among the prominent algorithms, Genetic Algorithms (GAs) emulate natural selection and evolution, excelling in exploring large solution spaces, particularly in engineering design, financial portfolio optimization, and machine learning model tuning.[2,7] Simulated Annealing (SA), inspired by metallurgical annealing, adeptly navigates complex, multi-dimensional landscapes, making it successful in combinatorial optimization, VLSI circuit design, and parameter estimation. Ant Colony Optimization (ACO), drawing inspiration from ant foraging behavior, solves combinatorial optimization problems like the traveling salesman problem (TSP) and job scheduling by using artificial ants to explore solution spaces and communicate solution quality through pheromone trails.[5,8] Particle Swarm Optimization (PSO), inspired by social behavior in birds or fish, proves effective in continuous and multi-modal optimization problems by having a population of particles cooperatively explore the solution space(3). Applications of PSO include optimizing neural networks, image processing filters, and control systems. These algorithms, with their diverse inspirations, strengths, and limitations, contribute significantly to advancements in fields such as engineering,image processing, finance, artificial intelligence, and more.[4]

These algorithms excel in designing efficient supply chain networks, fine-tuning machine learning models, and optimizing financial portfolios, contributing to innovation and problem-solving.[9] A key advantage lies in their ability to address intricate and dynamic scenarios, surpassing traditional optimization methods.[10] They exhibit resilience in ambiguous or imperfect information environments, adapting to uncertainties and responding effectively to changing conditions.[11] Nature-inspired optimization algorithms continue to gain attention for their versatility, and ongoing research is expected to yield novel and enhanced algorithms, expanding their capabilities and improving performance.[12] The continual refinement of these techniques holds the promise of widespread application across various domains, offering innovative solutions to complex problems(9). As researchers deepen their understanding of natural systems, the future holds the potential for these algorithms to achieve new heights in problem-solving prowess.[13]

This paper presents a swarm-intelligence metaheuristic algorithm called the Golden Eagle Optimization Algorithm (GEO). GEO draws inspiration from the hunting behaviors of golden eagles, incorporating intelligent adjustments in attack and cruise propensities to explore solution spaces efficiently. The GEO algorithm has two drawbacks: the first is, that the algorithm exhibited slower convergence rates, and the second is that, the time required to reach an optimal or near-optimal solution is a drawback, especially for computationally expensive problems. This paper introduces its enhancement by integrating a wavelet mutation strategy with a GEO algorithm called WMGEO to further improve its exploration capabilities.

The paper is structured as follows: Section 2 explains the Golden Eagle Optimization Algorithm (GEO). In Section 3, the concept of wavelet mutation is elaborated upon. Subsequently, Section 4 delves into the details of the Golden Eagle Optimization Algorithm with Wavelet Mutation (WMGEO). Section 5 presents the results and engages in a comprehensive discussion. Finally, Section 6 encapsulates the paper with a conclusive summary of the findings and contributions. This organization will give readers a thorough understanding of GEO, its integration with wavelet mutation, and the corresponding outcomes.

Golden egeal optimization (GEO)

The Golden Eagle Optimizer (GEO) algorithm provides a new way of natural optimization based on the hunting styles and behaviors of the unique Golden Eagle. Since the inception of the GEO algorithm in 2021, it has created a large amount of interest and excitement across a variety of distinct fields including engineering and computer science. As a newer member of the metaheuristic family of algorithms, the GEO is designed to solve optimization problems and can quickly provide a path to optimal solutions by balancing exploration and exploitation. Key features and concepts associated with Golden Eagle Optimizer are 9:

- **Golden Eagle Behavior**: The algorithm is inspired by the hunting behavior of golden eagles, which involves searching for prey in a way that balances covering a wide area (exploration) and homing in on potential targets (exploitation).
- **Operators**: Operators: GEO utilizes a range of operators (responsible for mimicking the hunting techniques employed by eagles), including swoop, glide, and approach. Operators facilitate the search process and contribute toward exploration of the solution space.
- **Objective Function**: GEO, like other optimization algorithms, requires an objective function that it will attempt to optimize. The objective function denotes the problem that needs to be solved, with the GEO algorithm iteratively modifying the to be

optimal candidates to determine the best values for the function.

- **Exploration and Exploitation**: GEO is designed to find a balance of exploration (to explore new areas of the solution space), and exploitation (to refine its search in areas where it has had success). Achieving this balance is important for finding high-quality solutions efficiently.
- **Parameter Tuning**: Like many metaheuristic algorithms, GEO often requires fine-tuning parameters to adapt to specific optimization problems.

The algorithm utilizes a subtle blend of both solitary and cooperative hunting techniques, deployed by Golden Eagles during their hunting activities. Mimicking the foraging behavior of the Golden Eagle, is the basis of the GEO algorithm's problem-solving approach. The GEO algorithm has been successfully applied to a variety of real-world optimization problems, from power systems to engineering design, and has shown strong results9. Its simplicity and ability to handle complex optimization problems make the method a good way to solve difficult realworld problems. The Golden Eagle Optimizer algorithm is done as follows: [9]

- **Initialization:** The GEO algorithm begins by randomly initializing a population of solutions within the search space. Each key represents a set of decision variables defining a potential optimization problem solution.
- **Selection of Golden Eagles:** In the GEO algorithm, several solutions are selected as "Golden Eagles" based on their fitness value. The fitness value of a solution is determined by evaluating the objective function of that solution.
- **Exploration:** The Golden Eagles then explore the search space for the optimal solution. They do these using different movement strategies, such as soaring, searching, or gliding. During this process, the Golden Eagles communicate with each other to share information about the search space and improve their search efficiency.
- **Exploitation:** The GEO algorithm employs an exploitation phase, where the Golden Eagles intensively search the regions around the best solutions. This allows them to converge towards the optimal solution quickly.
- **Update:** the population is updated after each iteration by replacing some current solutions with new solutions generated using the movement strategies employed by the Golden Eagles.
- **Termination:** The algorithm continues until a stopping criterion is met. This could be a maximum number of iterations or a certain level of convergence achieved.
- **Solution**: Finally, the GEO algorithm returns the best solution found during the search process as the optimal solution to the optimization problem.

Wavelet mutation

Wavelet mutation enhances their performance in optimization algorithms like genetic and particle swarm optimization. Wavelet mutation is a mathematical function intentionally utilized to create diversity in the population and avoid early convergence to non-optimal solutions. [13] The idea is inspired by the underlying wavelet functions, which are mathematical functions used to analyze and describe data structures. Wavelets, as mathematical functions, have key characteristics that allow them to provide variation and explore the solution space as a whole. [12] The concept of wavelet mutation relies on the principal ideas derived from wavelet theory, when wavelets are used to analyze and describe a data structure at various scales. In this case, wavelet mutation acts as a disrupting component in the search process. Random aspects introduced by wavelet mutation can extricate the optimization process from local optima, inducing the search process to new regions of the solution landscape. [14] Wavelet mutation contributes to a thorough investigation of possible solutions, including populations which is needed when trying to optimize complicated problems. Wavelet mutation exemplifies how wavelet theory can be flexible and broad in scope, expanding the utility of wavelets from a more common data analysis tool and applying it to computational optimization. By incorporating a mathematical theory into algorithm design, wasteful and obtuse optimization methods can also be developed. This development can be robust, versatile, and efficient, giving the way to tackle any number of additional tasks. The function of wavelet mutation demonstrates the influence of mathematics in optimization algorithms. Through the application of wavelet functions, this mutation will allow optimization algorithms to efficiently and effectively traverse more complex problem spaces, thereby finding better and more resilient solutions. [15] This wavelet mutation can be situated as a dynamic means of transformation that works on a solution's decision variables through wavelet functions, in consideration of the wavelet description. In general, this disruptive methodology applies wavelets, compact, localized functions that encode and convey characteristic parts of a signal, as tools for optimization algorithms to accomplish a manipulative task on a decision variable with highest fidelity. So, a methodical and exploratory strategy is needed, which means carefully investigating ways of setting up different situations to find the right situation suited to the peculiarities of each problem.[16] After the exploitation and exploration phase of the method, each person will have a chance to mutate using the wavelet mutation strategy. In the wavelet mutating, the mutation probability P is set. An individual does a more let wavelet mutation where rand P. The equation for mutation is:[17,18]

$$X_i^{new}(\mathrm{t}) = \begin{cases} X_i(t) + \sigma\,(UB - X_i(t)), & \text{rand} < 0.5 \\ X_i(t) + \sigma\,(X_i(t) - LB), & \text{rand} \geq 0.5 \end{cases} \tag{1}$$

Where LB and UB are the lower and upper boundaries of the current search space, and Xi(t)(i = 1, 2,_ _ _, N) represents the i-th individual location in the t-th generation. In line with this, σ represents the wavelet modifying coefficient. Its equation is:[17,19]

$$\sigma = \frac{1}{\sqrt{\alpha}}\,\psi\,\left(\frac{\varphi}{\alpha}\right) \tag{2}$$

Where $\psi(\frac{\varphi}{\alpha}) = e^{-(\frac{\varphi}{\alpha})^2}/2 * \cos(5\varphi/\alpha)$is the morlet wavelet function, and 99% of its energy can be concentrated within –2.5 and 2.5, so φ signifies an arbitrary number within –2.5 φ and 2.5 φ. The α is the scaling parameter, and its expression is:[17]

$$\alpha = S * \frac{1}{S}^{\left(1-\frac{t}{t_{max}}\right)} \tag{3}$$

Where S denotes a certain constant, after the wavelet mutation function is finished, the mutant individual X_i^{new} is gained, and a greedy choice can be made between the original individual X_i and mutant individual X_i^{new}, i.e.,[17,20]

$$X_i(\mathrm{t}+1) = \begin{cases} X_i^{new}(t), & \mathrm{f}(X_i^{new}(t)) \leq \mathrm{f}(X_i(t)) \\ X_i(t), & \mathrm{f}(X_i^{new}(t)) > \mathrm{f}(X_i(t)) \end{cases} \tag{4}$$

This process ensures that an individual with better fitness will enter the following iteration, increasing the algorithm's ability to optimize and accelerate convergence.

Improved golden eagle optimization algorithm using wavelet mutation (WMGEO)

The Golden Eagle Optimization (GEO) Algorithm is a swarm intelligence, nature-inspired method that mimics the hunting association of eagles. This algorithm simulates a group of eagles where each eagle represents a solution to a problem. In this circumstance, the eagles share information and together decide on where and how to orient their eventual location to find the solution. In traditional GEO, the algorithm uses uniform distributions to regulate parameters that associate with the attack, cruise positions and step vectors. This paper proposes a new extension called WMGEO (Wavelet Mutation Golden Eagle Optimization) with the intention of improving the algorithms performance. WMGEO employs randomness by using wavelet mutation techniques where the attack, cruise and step vectors are randomized using wavelet mutations. The addition of wavelet mutations is an effective procedure for increasing diversification and exploration within the optimization process. The addition of wavelet mutation incorporates a stochastic element to the search process. This allows the algorithm to move away from local optima and explore the solution space effectively. Algorithm 1 along with Fig. 1 provided a complete outline of the enhanced WMGEO algorithm, which shows the use of wavelet mutation to enhance the optimization of the algorithm. It should be noted that selecting the appropriate wavelet function and optimizing the associated parameters is important to improve the performance of the new algorithm. These considerations should not be overlooked to ensure the algorithm's applicability to many problem contexts and utility for solving complex optimization problems. Through this process, we have provided readers with a complete understanding of the GEO algorithm and how it can be integrated with wavelet mutation and to be applied in numerous problem-solving environments.

Results and discussion

The proposed Wavelet Mutation Golden Eagle Optimization (WMGEO) algorithm is evaluated, in a comprehensive use case, using the CEC2017 benchmark test function set. The CEC2017 benchmark is well-organized into three categories, with each intended to evaluate an attribute of optimization performance. The first category is the symmetric unimodal functions (f1 to f7) and are characterized by a single minimum. These models provide the first basic performance benchmark to set for the algorithm to evaluate the performance characteristics in addressing simpler single-peaked optimization problems. The second category is multimodal function set and includes, multiple local minima (f8 to f13) and introduces a problem space with multiple local optima. This category is useful for evaluating the algorithm's ability to search through a solution space that includes local extrema. The third and hardest category is multimodal functions with many local minima (f14 to f18). This poses a significant challenge to

Algorithm 1: Improved golden eagle optimization (WMGEO).

Initialize the populationof golden eagles
Evaluate fitness function
Initialize population memory
Initialize *pa* and *pc*
Initialize T (the number of iterations)
for each iteration t
    Update p_a and p_c

$$p_a = p_a^0 + \frac{t}{T}\left[p_a^T - p_a^0\right] \tag{5}$$

$$p_c = p_c^0 + \frac{t}{T}\left[p_c^T - p_c^0\right] \tag{6}$$

    for each golden eagle i
        Randomly select a pair of prey from the population's memory as parent
        Perform wavelet mutation on the parent eagles to produce offspring eagle.
        Evaluate the fitness of the offspring eagle.
        Select the best eagle among the parent and offspring eagle,
        Replace the worst eagle in the population with best eagle.
        Calculate attack vector $\vec{A_i}$

$$\vec{A_i} = \vec{X}_f^* - \vec{X_i} \tag{7}$$

        if attack vector's length is not equal to zero
            Calculate cruise vector $\vec{C_i}$

$$\vec{C_i} = \left(C_1 = random,\ C_2 = random, \ldots, C_k = \frac{d - \sum_{j,\, j \neq k} a_j}{a_k}, \ldots, C_n = random\right) \tag{8}$$

            Calculate step vector Δx

$$\Delta X_i = \vec{r}_1\, p_a \frac{\vec{A_i}}{\|\vec{A_i}\|} + \vec{r}_2\, p_c \frac{\vec{C_i}}{\|\vec{C_i}\|} \tag{9}$$

            $\vec{r}_1$ and $\vec{r}_2$ are random vectors whose elements lie in the interval [0,1]
            Update position

$$X^{t+1} = X^t + \Delta X_i^t \tag{10}$$

            Evaluate fitness function for the new position
            if fitness is better than the fitness of the position in eagle i's memory
                Replace the new position with the position in eagle i's memory
            end
        end
    end
end

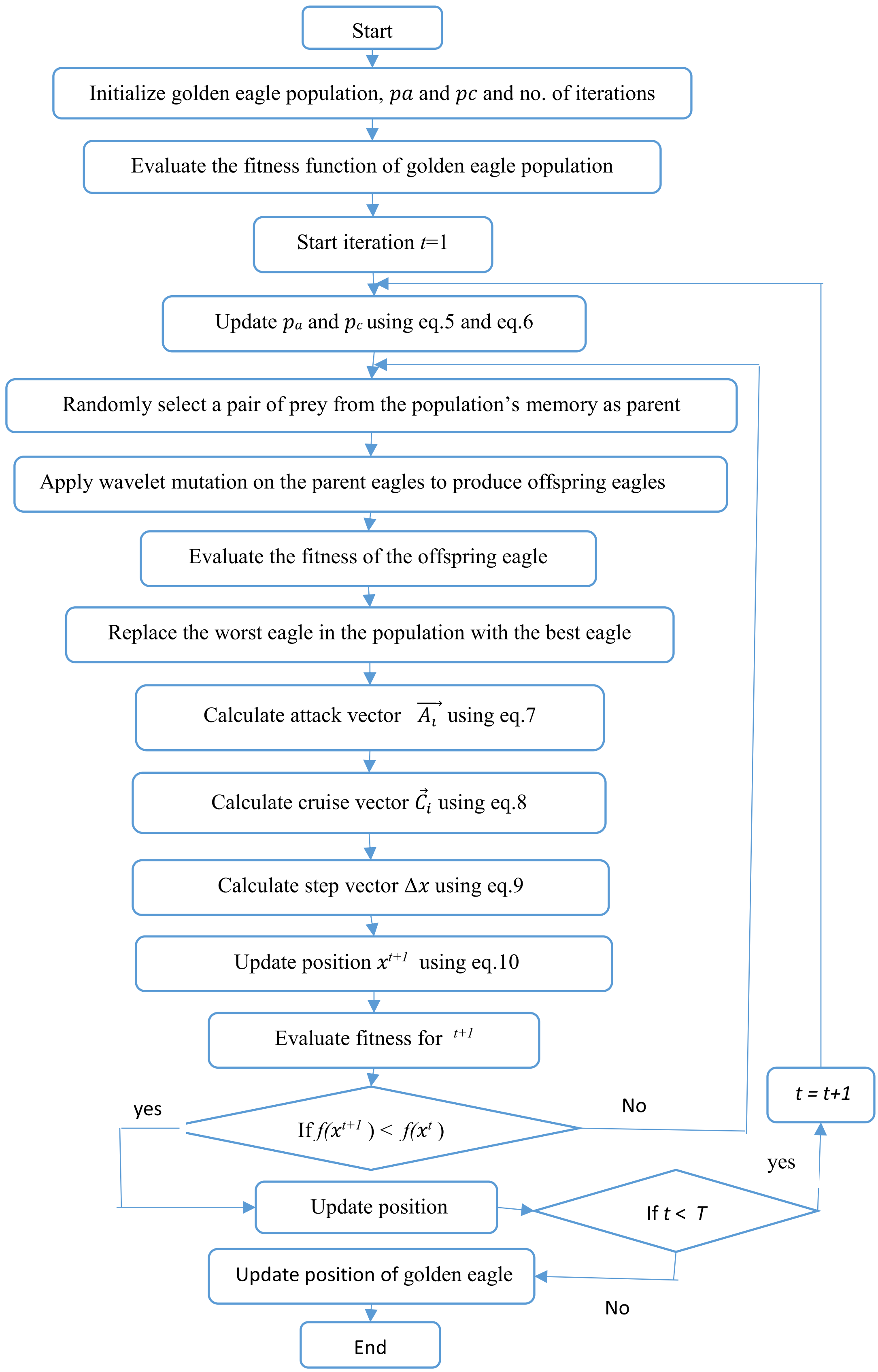

Fig. 1. Flowchart of improved golden eagle optimization (WMGEO).

Table 1. The expressions of benchmark test functions.

Expression		Domain Range
$F_1(x) = \sum_{i=1}^{30} x_i^2$	(11)	$-100 \le x_i \le 100$
$F_2(x) = \sum_{i=1}^{9} [100\,(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	(12)	$-2.048 \le x_i \le 2.048$
$F_3(x) = \sum_{i=1}^{100} (\lvert x_i + 0.5\rvert)^2$	(13)	$-10 \le x_i \le 10$
$F_4(x) = \sum_{i=1}^{10} i x_i^4 + \mathbf{random}[0,1)$	(14)	$-2.56 \le x_i \le 2.56$
$F_5(x) = \mathbf{max}\{\lvert x_i\rvert, \; 1 \le i \le 30$	(15)	$-100 \le x_i \le 100$

Table 2. The experimental results.

		GEO	WMGEO
F1	*Mean*	6.6789195120570755	32.700494744084125
	Std	9.725413293102266	0.07124691010136079
F2	*Mean*	2967.2152540675506	8901.780110527163
	Std	6204.110559422709	311.93780797638163
F3	*Mean*	0.0701415636663623	0.11013674472907806
	Std	0.1886658093040894	0.05450853831155062
F4	*Mean*	6.475078814208489	12.590646463046882
	Std	9.001393037672695	3.1183081539448843
F5	*Mean*	2664.2837085620936	1795.3758545029473
	Std	2687.90333872731	115.77871104991053

optimization which is required to operate in an optimization landscape containing many local optima thus testing the algorithm's ability to explore different solution space. The expressions for these benchmark test functions are provided in Table 1. This paper examines the performance of WMGEO using five benchmark functions chosen from the unimodal function category. These benchmark functions are purposefully chosen to give a range of optimization problems to allow for an informal evaluation of the WMGEO algorithm.

The performance of the GEO and the proposed WMGEO on solving the benchmark test functions are evaluated, and the following simulation conditions are used:

- Swarm size: 50
- Number of iterations: 100
- Parameter settings: *pa*: Propensity to attack [0.5–2]
  pc: Propensity to cruise [1–0.5]

To demonstrate the benefits of the GEO and WMGEO were applied to the six benchmark test functions in this section. Table 2 summarizes the experimental findings regarding the mean value and standard deviation.

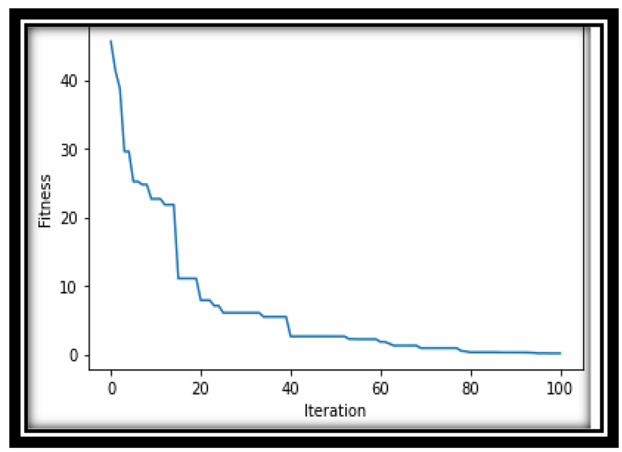

Fig. 2. Applied GEO on function 1.

- ***Function f1***: The most often used function is undoubtedly function f1, a spherical model. This function, which measures the rate of searching convergence, is symmetric and smooth. The outcomes of this function are significantly superior to the GEO in terms of the mean value of the WMGEO. The substantially lower standard deviation indicates that the solutions are more stable. Due to its superior searching capabilities, the WMGEO exhibits a faster convergence rate than other approaches, as shown in Figs. 2 and 3.
- ***Function f2:*** A strongly non-separable generalized Rosenbrock's function, function f2 has an optimal location in a relatively small ridge. The ridge travels around a parabola and has an extremely pointed tip. Regarding mean value and standard deviation, the WMGEO outperforms the GEO. Additionally, as shown in Figs. 4 and 5, the WMGEO has a good convergence rate.
- ***Function f3:*** A function that represents flat surfaces is function f3. Because they provide no clues

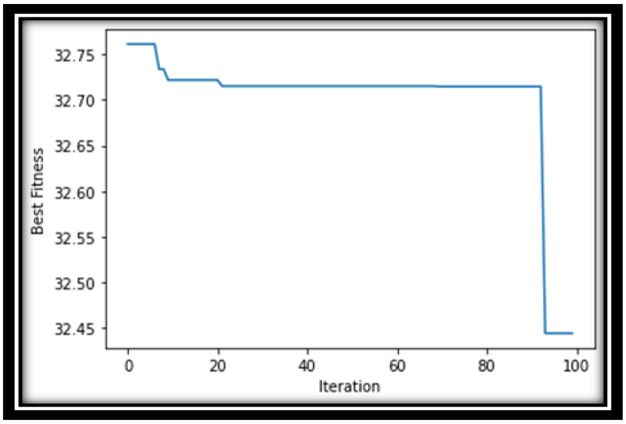

Fig. 3. Applied WMGEO on function 1.

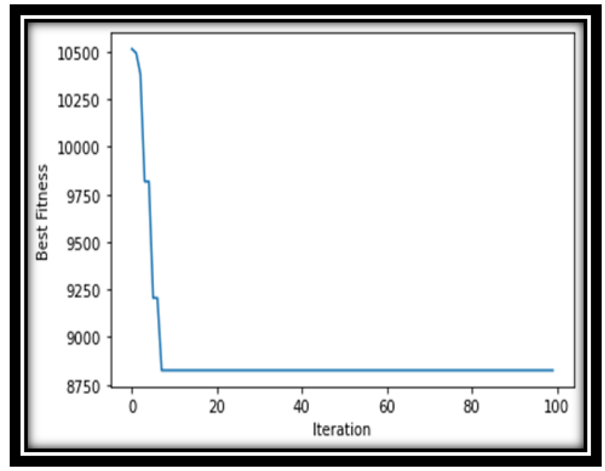

Fig. 5. Applied WMGEO on function 2.

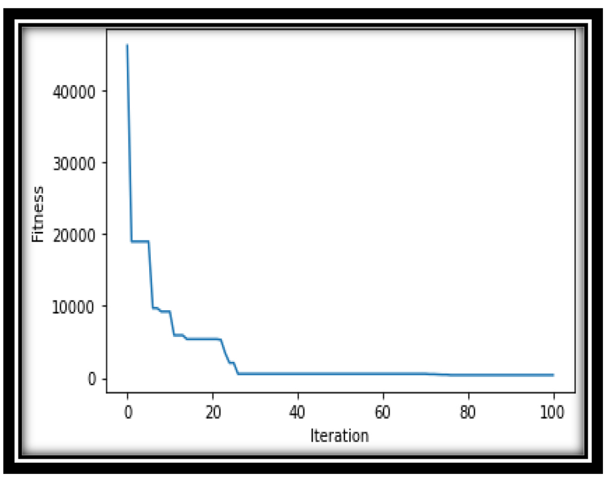

Fig. 4. Applied GEO on function 2.

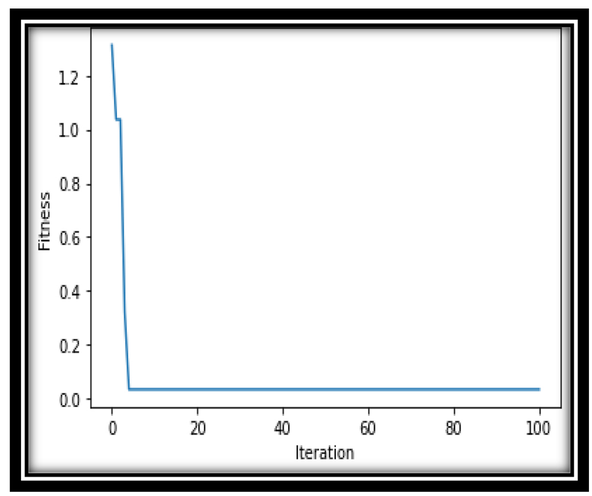

Fig. 6. Applied GEO on function 3.

as to the direction of the search, flat surfaces present challenges for algorithms used for optimization; the algorithm may become trapped in one of the flat surfaces if it doesn't have flexible step sizes. The WMGEO performs this purpose well because, as illustrated in Figs. 6 and 7, it can produce a lengthy jump via mutation processes.

- ***Function f4***: As a quadratic function with noise padding, function f4 makes it more challenging to find the minimum value because it never returns the same value at the same location. Figs. 8 and 9 illustrate how the WMGEO provides the best mean cost value compared to GEO.
- ***Function f5:*** Function f5 is Schwefel's problem; the mean value of the WMGEO is slightly lower than that of the GEO, but the standard derivation of the WMGEO is the best, as shown in Figs. 10 and 11.

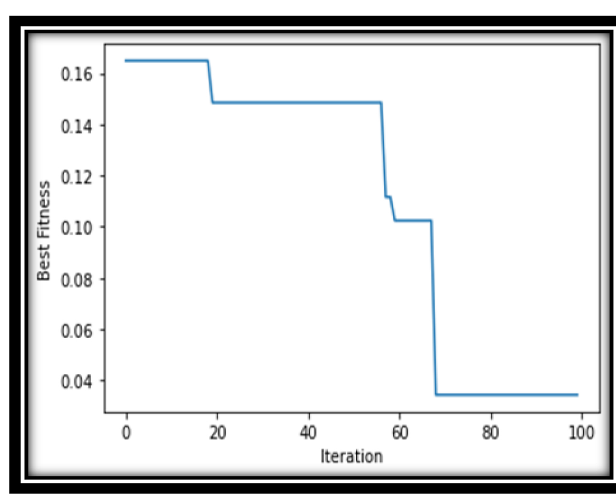

Fig. 7. Applied WMGEO on function 3.

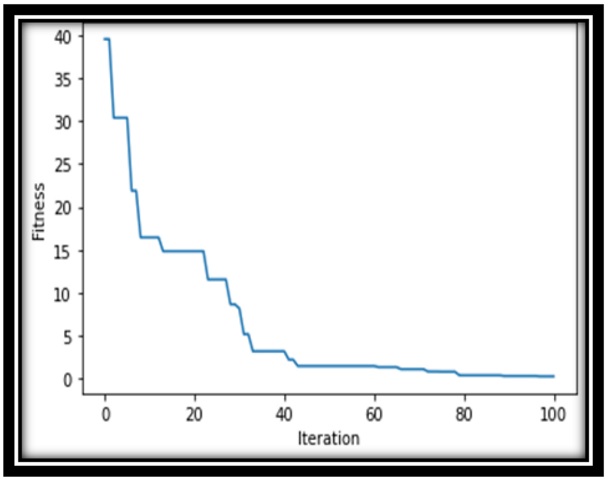

Fig. 8. Applied GEO on function 4.

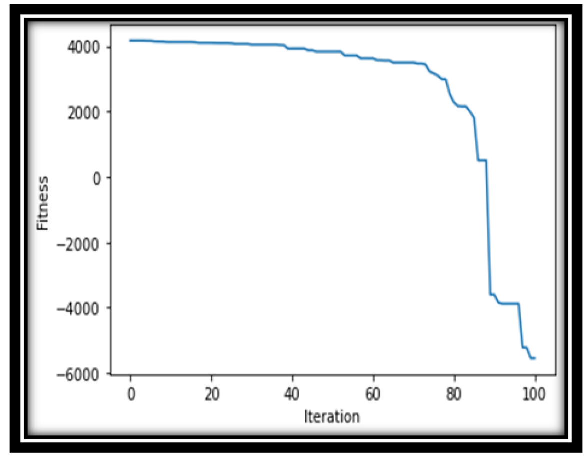

Fig. 10. Applied GEO on function 5.

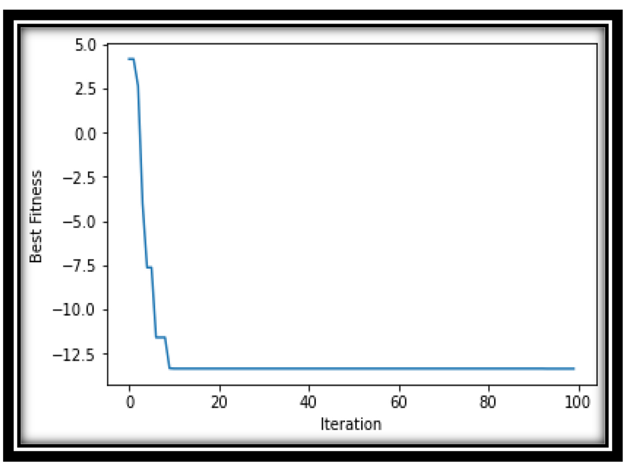

Fig. 9. Applied WMGEO on function 4.

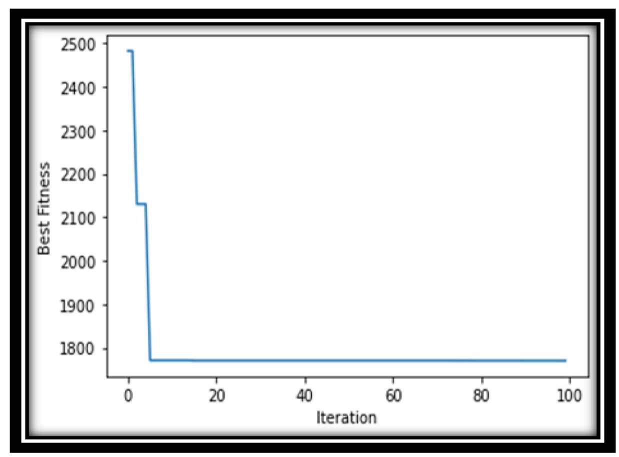

Fig. 11. Applied WMGEO on function 5.

The study's outcomes suggest that the Wavelet Mutation Golden Eagle Optimization Algorithm (WMGEO) outperformed the conventional Golden Eagle Optimization (GEO) algorithm across all tested benchmark functions. WMGEO achieved higher mean values and exhibited smaller standard deviation values, which imply improved convergence and consistency compared to GEO. Consequently, WMGEO offers enhanced solution quality and stability. In summary, the results indicate that integrating wavelet mutation into the golden eagle optimization algorithm has significantly improved performance when applied to these benchmark functions.

Conclusion

This paper describes a new method called Wavelet Mutation Golden Eagle Optimization (WMGEO), which aims to enhance the traditional Golden Eagle Optimization (GEO) algorithm's performance utilizing wavelet theory. There are two main weaknesses of the GEO algorithm are that it has a slow convergence rate and a long computational time to provide the optimal or near-optimal solution, which aggravates matter since some problems require high computational effort. Thus, this paper's focus is to improve GEO's ability to investigate the solution space more effectively, so that it produces an accurate and efficient problem solution. Based on the thorough simulations, this proposed WMGEO algorithm is an important tool for solving optimization problems. The hybrid GEO relies upon the basic properties of wavelets to demonstrably enhance and stabilize the quality of solutions for different benchmark test functions. It has been established through extensive trials that the proposed WMGEO consistently dominates the GEO algorithm in a variety of situations, especially in terms of convergence rates, quality of solutions, and overall optimization success. The results represent the considerable gains made from the WMGEO approach and its ability to outperform conventional GEO algorithms for practical optimization problems. Future work will examine the sensitivity of WMGEO to adjustments in parameters and utilize the WMGEO algorithm on real-world optimization problems in image processing, finance, and healthcare.

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for republication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at Ministry of Higher Education and Scientific Research, Iraq.

Authors' contribution statement

E.T. contributed to the design and drafting of the MS, A.S.J. contributed revision and proofreading and N. F. H. contributed analysis of the results.

References

1. Salgotra R, Singh U. A novel bat flower pollination algorithm for synthesis of linear antenna arrays. Neural Comput Appl. 2018;30:2269–82. https://doi.org/10.1007/s00521-016-2833-3.
2. Salgotra R, Singh U, Saha S. On some improved versions of whale optimization algorithm. Arab J Sci Eng. 2019;44:9653–91. https://doi.org/10.1007/s13369-019-04016-0.
3. Singh U, Salgotra R. Synthesis of linear antenna arrays using enhanced firefly algorithm. Arab J Sci Eng. 2019;44:1961–76. https://doi.org/10.1007/s13369-018-3214-2.
4. Jain N, Nangia U, Jain J. A review of particle swarm optimization. J Inst Eng (India): B 2018;99:407–11. https://doi.org/10.1007/s40031-018-0323-y.
5. Alsattar HA, Zaidan A, Zaidan B. Novel meta-heuristic bald eagle search optimisation algorithm. Artif Intell Rev. 2020;53:2237–64. https://doi.org/10.1007/s10462-019-09732-5.
6. Hashim FA, Hussain K, Houssein EH, Mabrouk MS, Al-Atabany WJAI. Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems. Appl Intell. 2021;51:1531–51. https://doi.org/10.1007/s10489-020-01893-z.
7. Faramarzi A, Heidarinejad M, Stephens B, Mirjalili S. Equilibrium optimizer: A novel optimization algorithm. Knowl B S. 2020;191:105190. https://doi.org/10.1016/j.knosys.2019.105190.
8. Nematollahi AF, Rahiminejad A, Vahidi B. A novel metaheuristic optimization method based on golden ratio in nature. Soft Comput. 2020;24:1117–51. https://doi.org/10.1007/s00500-019-03949-w.
9. Mohammadi A, Nayeri M, Azar A, Taghizadeh M, Engineering I. Golden eagle optimizer: A nature-inspired metaheuristic algorithm. Comput Ind Eng. 2021;152:107050. https://doi.org/10.1016/j.cie.2020.107050.
10. Rakotonirainy RG, Vuuren J. Improved metaheuristics for the two-dimensional strip packing problem. Comput Ind Eng . 2020;92:106268. https://doi.org/10.1016/j.asoc.2020.106268.
11. Wagan AI, Shaikh MM. A new metaheuristic optimization algorithm inspired by human dynasties with an application to the wind turbine micrositing problem. Appl Soft Comput. 2020;90:106176. https://doi.org/10.1016/j.asoc.2020.106176.
12. Zhang Y, Jin Z. Group teaching optimization algorithm: A novel metaheuristic method for solving global optimization problems. Expert Syst Appl. 2020;148:113246. https://doi.org/10.1016/j.eswa.2020.113246.
13. Hayyolalam V, Kazem A. Black widow optimization algorithm: a novel meta-heuristic approach for solving engineering optimization problems. Eng Appl Artif Intell. 2020;87:103249. https://doi.org/10.1016/j.engappai.2019.103249.
14. Alangari S, Obayya M, Gaddah A, Yafoz A, Alsini R, Alghushairy O. Wavelet mutation with Aquila optimization-based routing protocol for energy-aware wireless communication. Sensors. 2022;22(21):8508. https://doi.org/10.3390/s22218508.
15. Hu G, Du B, Li H, Wang X. Quadratic interpolation boosted black widow spider-inspired optimization algorithm with wavelet mutation. Math Comput Simul. 2022;200:428–67. https://doi.org/10.1016/j.matcom.2022.04.031.
16. Mukherjee V, Mukherjee A, Prasad D. Whale optimization algorithm with wavelet mutation for the solution of optimal power flow problem. Handbook of research on predictive modeling and optimization methods in science and engineering: IGI Global; 2018;500–53. https://doi.org/10.4018/978-1-5225-4766-2.ch023.
17. Ma L, Li J, Zhao YJF. Population forecast of China's rural community based on CFANGBM and improved Aquila optimizer algorithm. Fractal and Fractional. 2021;5(4):190. https://doi.org/10.3390/fractalfract5040190.
18. Mahmood RAR, Abdi A, Hussin M. Performance Evaluation of Intrusion Detection System using Selected Features and Machine Learning Classifiers. Baghdad Sci J. 2021;18(2):0884 https://doi.org/10.21123/bsj.2021.18.2(Suppl.).0884.
19. Iqbal Z, Ilyas R, Chan HY, Ahmed N. Effective Solution of University Course Timetabling using Particle Swarm Optimizer based Hyper Heuristic approach. Baghdad Sci J. 2021;18(4):1465. https://doi.org/10.21123/bsj.2021.18.4(Suppl.).1465.
20. Talib E, Hassan N F, Jamil A S. The Defensive Methods Against Deepfake: Review. Iraqi J Sci. 2023;64(10):5345–5357. https://doi.org/10.24996/ijs.2023.64.10.39.

تحسين خوارزمية النسر الذهبي من خلال استخدام طفرة المويجات

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2قسم هندسة تقنيات الحاسوب ، كلية المنصور الجامعية ، العراق

3قسم علوم الحاسوب ، الجامعة التكنولوجية ، بغداد ، العراق

الخلاصة

تعتبر خوارزمية تحسين النسر الذهبي (GEO) بمثابة تقنية تحسين رائعة مستوحاة من الطبيعة، وتستمد إشاراتها من براعة صيد النسور الذهبية في الطبيعة. تقدم هذه الخوارزمية محاكاة آسرة لكيفية تعاون هذه الطيور المهيبة للبحث عن الفريسة، وذلك باستخدام مجموعة من "النسور" الافتراضية، والتي يمثل كل منها حلاً محتملاً لمشكلة التحسين. تتواصل هذه النسور وتتبادل المعلومات وتنسق تحركاتها بشكل جماعي، كل ذلك سعيًا لتحقيق الهدف النهائي - الحل الأمثل للمشكلة. تأخذ هذه الدراسة الابتكار إلى أبعد من ذلك من خلال تقديم تطوير خوارزمية GEO، وهي Wavelet Mutation Golden Eagle Optimization (WMGEO). تقوم WMGEO بدمج وظيفة طفرة المويجات في إطار عمل GEO، مما يؤدي إلى إثراء قدرات الاستكشاف والأداء العام عند مواجهة تحديات التحسين المعقدة. الهدف الأساسي لـ WMGEO هو معالجة بعض القيود الكامنة في خوارزمية GEO الأصلية. وعلى وجه الخصوص، فإنه يؤكد بقوة على تحسين جودة الحلول، وتعزيز سرعة التقارب، وتعزيز استقرار الحلول. لإجراء تقييم دقيق لفعالية هذا النهج المقترح، يتم استخدام مجموعة من وظائف الاختبار المعياري. تشمل وظائف الاختبار هذه فئات مختلفة، وتقدم مجموعة متنوعة وشاملة من التحديات لـ WMGEO. ترسم النتائج التجريبية التي تم الحصول عليها من خلال هذه التقييمات صورة مقنعة لبراعة الخوارزمية. بالمقارنة مع خوارزمية GEO القياسية، هناك تحسينات كبيرة في جودة الحل وسرعة التقارب واستقرار الحل. تؤكد هذه النتائج على إمكانات WMGEO كأداة قوية في التحسين، وإظهار قدرتها على التفوق على سابقتها في سيناريوهات مختلفة لحل المشكلات.

الكلمات المفتاحية: وظيفة الاختبار المعياري، تحسين النسر الذهبي، مستوحاة من الطبيعة، الانحراف المعياري، طفرة المويجات.