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Research Paper

Sayısal Global Optimum için Çift-Girişim Tabanlı İyileştirme Algoritmasının Yakınsama Analizi

Convergence Analysis of Bi-Attempted Based Optimization Algorithm for Numerical Global Optimum

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Özetçe—Bu çalışmada, yeni geliştirilen Çift-Girişim Tabanlı İyileştirme Algoritması (ABaOA)'nın arama yaklaşım özellikleri altı hörgüçlü deve fonksiyonunda gösterilmiştir. Altı yerel minimum ve iki küresel minimum ile altı hörgüçlü deve fonksiyonu, optimizasyon tekniklerinin etkinliğini değerlendirmek için kullanılan iyi bilinen sabit boyutlu multimodel kalite testi fonksiyonlarından biridir. Gerçek dünya sayısal optimizasyon sorunları hızlı işleme süreleri gerektirir, bu nedenle ABaOA bu referans fonksiyonu üzerinde test edilmesi tasarlanmıştır. Deneylerden elde edilen sonuçlar hız ve uygulanabilirlik açısından umut vericidir. Yüksek verimli arama algoritması ABaOA, işlevsel bir çözüm sağlar ve aynı zamanda hızlı bir şekilde küresel optimum çözümü bulur.

Anahtar Kelimeler : *Bilgisayar zekası, evrimsel algoritmalar, iyileştirme problemleri*.

Abstract—In this study, the search convergence properties of a recently developed Bi-Attempted Based Optimization Algorithm (ABaOA) on a six-hump camel function are demonstrated. The six-hump camel function, with its six local minima and two global minima, is one of the well-known fixed-dimension multimodal benchmark functions used to assess the effectiveness of optimization techniques. The ABaOA is intended to be tested on this benchmark function because real-world numerical optimization problems necessitate quick processing times. Results that are obtained from experiments are promising in terms of speed and viability. The highly effective search algorithm ABaOA ensures a workable solution while also quickly arriving at the global optimal solution.

Keywords: *Computational intelligence, evolutionary algorithms, optimization problems*.

1. Introduction

Optimization problems are caused by aiming to achieve objectives efficiently, and these problems consist of objective and constraint elements with some solutions being better than others. However, seeking to accomplish goals effectively, leads to optimization challenges. Some solutions can be considered preferable to others for some situations. In such cases, the best choice may be the optimal global solution.

There are several recent studies seeking to reach global optimum solutions for real-life problems such as renewable energy resources. Stall-Induced Vibrations (SIV) are crucial for wind turbine blade design, affecting inflow and structural characteristics. Studying SIV requires high computational costs and input variables. This work adopted a Surrogate-Based Optimization (SBO) framework, validating against the Six-Hump Camel function and the Rosenbrock function (Santhanam et al., 2023).

Several metaheuristic algorithms are introduced recently. A three-on-three optimizer (TOTO), a swarm intelligence-based metaheuristic that adopts multiple searches into a single mechanism is one of them which is introduced by Daru Kusuma, Dinimaharawati, (2023). TOTO found as powerful in solving high-dimension unimodal, multimodal, and fixed-dimension multimodal problems. TOTO metaheuristic outperforms previous methods and finds acceptable solutions in low iteration and population size situations.

The numerical results on test problems were improved by a modified q-BFGS approach that respects global convergence qualities without making any convexity assumptions. In chemical research, optimization is vital for reducing energy consumption, creating fluid flow systems that are optimal, improving product concentration and reaction speed, and improving separation processes (Lai et al., 2023).

Another recent study about the improvement of the existing optimization algorithm is the FO-JAYA algorithm to fractional-order conceptual theory using a meta-heuristic algorithm, evaluating solar unpredictability, biomass planning, stochastic reliability, and optimal-economic decision-making using nine solar probabilistic classes. Four different test functions were investigated to verify the global solution achievement and accuracy of the proposed FO-JAYA. These two global optimization test functions; the three-hump camel function and the Six-hump camel function, have been considered for the efficacy of the algorithm to avoid local minima and achieve a global solution (Kumar et al., 2023).

The convergence analysis of Gamma-Based Particle Swarm Optimization (GbPSO) was tested using numerical simulations, and the majority of parameter combinations yielded positive results. In terms of convergence velocity, the GbPSO outperformed the regular Particle Swarm Optimization (PSO) in terms of average cost value and successful runs. Both algorithms failed to converge the benchmark functions Sphere and Three-hump Camel (Loui Mar et al., 2022).

Recent studies showed that the Six-Hump Camel function is a widely used benchmark function to validate an optimization algorithm. The ABaOA was implemented in two case study problems in (Yildiz et al., 2023), and encouraging results were obtained. ABaOA outperforms Genetic Algorithm and BaOA in search convergence, reaching global optimum faster than Base Optimization Algorithm (BaOA) and Genetic Algorithms (GA) (Köse Ulukök, 2023).

In this study, by considering the importance of a fast numerical optimization process on real-life problems the ABaOA convergence analysis is decided to be performed on the Six-Hump Camel function.

2. Method

ABaOA is developed by Köse Ulukök, (2021) by adapting the Base Optimization Algorithm (BaOA). It is a population-based algorithm that uses arithmetic operators to guide its candidate solutions to the optimum solution. According to it, a number of candidate solutions are produced at the beginning of the first iteration. Then, the corresponding fitness function values for each individual are estimated. The best individual is carried to the next iteration.

The ABaOA algorithm flowchart is given in Figure 1. Population size defines the number of individuals, and they are randomly generated (Si). Then, the fitness value of each individual (f(Si)) is calculated, where f is the test function. The individual who has the best fitness score is recorded. For each individual, mutation operators are applied by using two displacement parameters, δ1, and δ2 respectively. Then, the individuals for the next generation are obtained (Si+, Si++, Si-, Si--) within the minimum and maximum ranges (Rmin and Rmax). Then, as the final step of the algorithm, the fitness values for each individual are calculated, and the best individual is updated.

Multimodal benchmark functions can also be optimized using the ABaOA in addition to unimodal benchmark functions. It converges on the global optimum for both types of functions quickly (Köse Ulukök, 2023).

3. Results

The six-hump camel function is widely used as a benchmark problem for optimization algorithms and as a challenging test for their capability and efficacy to find the global minimum within the complex landscape of local minima and maxima. The function domain is usually considered on the intervals $x1 \in [-3, 3]$ and $x2 \in [-2, 2]$. This function has six local minima and two global minima as -1.0316 located at (0.0898, -0.7126) and (-0.0898, 0.7126). The function graph and the formula are shown in Figure 2.

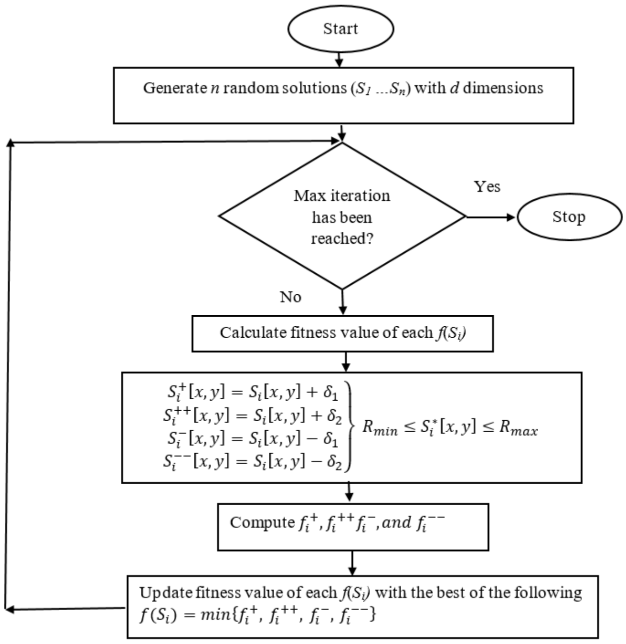
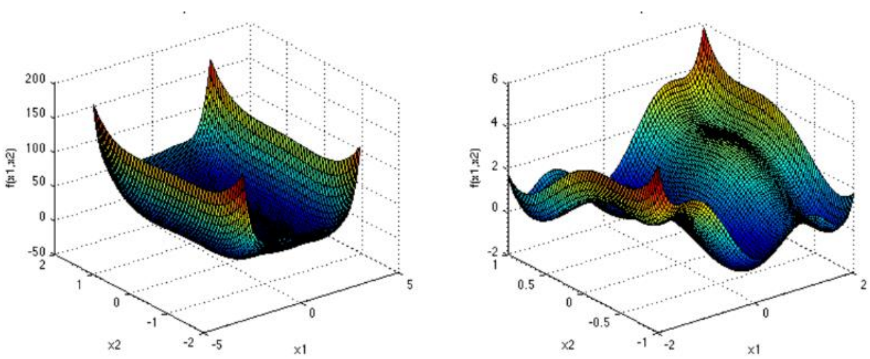


Figure 1. ABaOA Flow Chart



$$f(\mathbf{x}) = \left(4 - 2.1x_1^2 + \frac{x_1^4}{3}\right)x_1^2 + x_1x_2 + (-4 + 4x_2^2)x_2^2$$

Figure 2. The six-hump camel function (Lai et al., 2023)

A search space exploration of the six-hump camel function by optimization algorithms is illustrated in Figure 3. The Minimum_X_value represents x1, and the Minimum_Y_value represents x2. Potential solution points on the search space are represented with black dots.

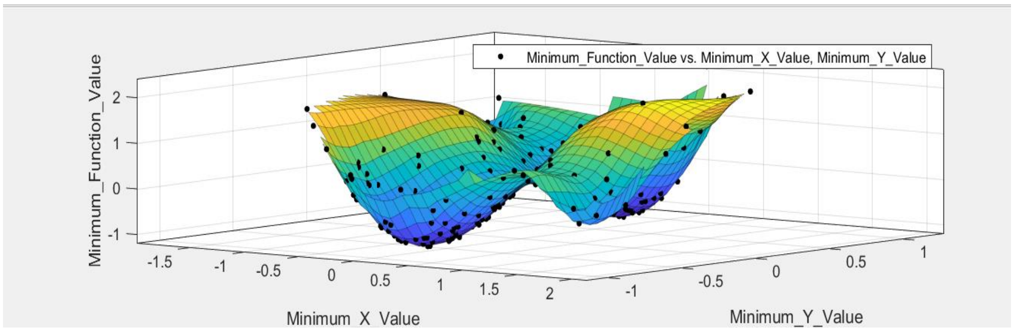


Figure 3. Six-Hump Camel function search space with random solutions

The ABaOA (Köse Ulukök, 2023), the TOTO (Daru Kusuma, Dinimaharawati, 2023), the JAYA and the FO-JAYA (Kumar et al., 2023) parameter settings are summarized in Table 1. Unavailable fields are kept as empty in the table.

Table 1. Referenced algorithms' parameter settings

Algorithm	Population Size	Max Iteration	δ1	δ2
ABaOA	10	25	0.01	0.05
TOTO	10	50	-	-
JAYA	-	60	-	-
FO-JAYA	-	60	-	-

The ABaOA (Köse Ulukök, 2023), the TOTO (Daru Kusuma, Dinimaharawati, 2023), the JAYA and the FO-JAYA (Kumar et al., 2023) performance results on the Six-Hump Camel function are given in Table 2. The ABaOA average and standard deviation are calculated out of 10 independent runs.

Table 2. Six-Hump Camel test function results

Algorithm	Avg	STD
ABaOA	-1.0316	0,0000422
JAYA	-1.029	0.00209
FO-JAYA	-1.031	0.00112
TOTO	-1.0316	0

The ABaOA (Köse Ulukök, 2023) convergence performance for the Six-Hump Camel function is shown in Figure 4. As it is clearly seen in the graph, the ABaOA reaches the global optimum value within the first eleventh iteration. The function parameters x1 and x2 are unchanged up to the end of the maximum iteration number.

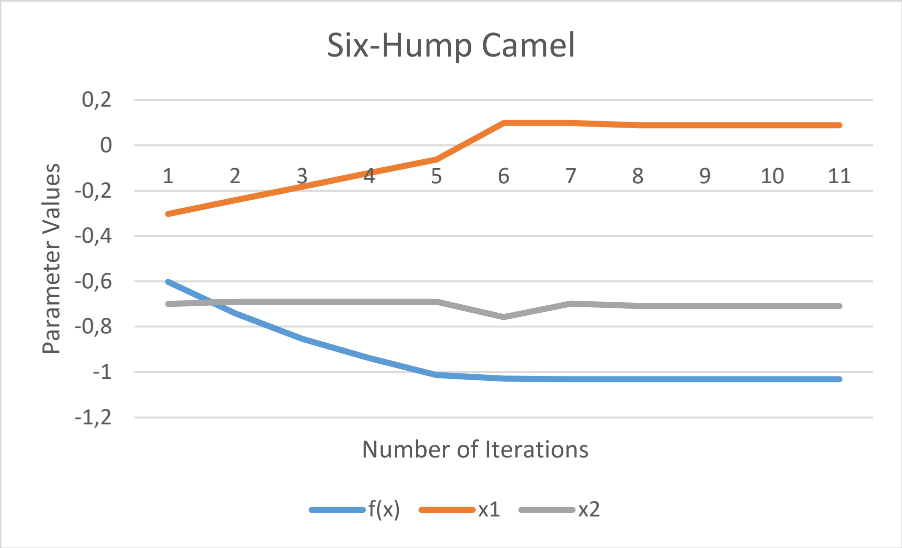


Figure 4. ABaOA convergence for Six-Hump Camel function

4. Sonuç

ABaOA is a population-based algorithm that uses arithmetic operators to guide candidate solutions to the optimum solution. It generates multiple solutions, estimates fitness function values, and transfers the best to the next iteration.

The ABaOA algorithm uses a population size of individuals (Si) to generate fitness values. The best fitness score is recorded, and mutation operators are applied. Next-generation individuals are obtained within minimum and maximum ranges (Rmin and Rmax). Fitness values are calculated and updated.

ABaOA optimizes multimodal benchmark functions and converges quickly to the global optimum for both types. The convergence performance of the ABaOA for the Six-Hump Camel function shows that it converges to the global optimum faster than the TOTO (Daru Kusuma, Dinimaharawati, 2023), the JAYA and the FO-JAYA (Kumar et al., 2023). The ABaOA reaches the global optimum value within the first eleven iterations, as is evident from the convergence graph.

Kaynaklar

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