Enhanced Variants of Crow Search Algorithm Boosted with Cooperative Based Island Model for Global Optimization

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Abstract

The Crow Search Algorithm (CSA) is a swarm-based metaheuristic algorithm that simulates the intelligent foraging behaviors of crows. While CSA effectively handles global optimization problems, it suffers from certain limitations, such as low search accuracy and a tendency to converge to local optima. To address these shortcomings, researchers have proposed modifications and enhancements to CSA's search mechanism. One widely explored approach is the structured population mechanism, which maintains diversity during the search process to mitigate premature convergence. The island model, a common structured population method, divides the population into smaller independent sub-populations called islands, each running in parallel. Migration, the primary technique for promoting population diversity, facilitates the exchange of relevant and useful information between islands during iterations. This paper introduces an enhanced variant of CSA, called Enhanced CSA (ECSA), which incorporates the cooperative island model (iECSA) to improve its search capabilities and avoid premature convergence. The proposed iECSA incorporates two enhancements to CSA. Firstly, an adaptive tournament-based selection mechanism is employed to choose the guided solution. Secondly, the basic random movement in CSA is replaced with a modified operator to enhance exploration. The performance of iECSA is evaluated on 53 real-valued mathematical problems, including 23 classical benchmark functions and 30 IEEE-CEC2014 benchmark functions. A sensitivity analysis of key iECSA parameters is conducted to understand their impact on convergence and diversity. The efficacy of iECSA is validated by conducting an extensive evaluation against a comprehensive set of well-established and recently introduced meta-heuristic algorithms, encompassing a total of seventeen different algorithms. Significant differences among these comparative algorithms are established utilizing statistical tests like Wilcoxon's rank-sum and Friedman's tests. Experimental results demonstrate that iECSA outperforms the fundamental ECSA algorithm on 82.6% of standard test functions, providing more accurate and reliable outcomes compared to other CSA variants. Furthermore, Extensive experimentation consistently showcases that the iECSA outperforms its comparable algorithms across a diverse set of benchmark functions.

Keywords: Crow search algorithm, Island model, Tournament selection, Population diversity, Metaheuristics

1. Introduction

Optimization algorithms encompass a broad range of methods, including deterministic, evolutionary, and swarm-based techniques Cao et al. (2019b). These algorithms are designed to address

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objective functions, which can be categorized as single-objective or multi-objective Lu et al. (2023b) or many-objective Cao et al. (2020b). Additionally, various forms of optimization, such as robust optimization and distributed optimization Li et al. (2022), have been developed to cater to specific requirements and challenges in the field of optimization. Combinatorial optimization problems, including scheduling, routing, and decision problems, are predominantly classified as NP-complete or NP-hard problems Cao et al. (2020a); Duan et al. (2023); Lv et al. (2022). Traditional mathematical programming techniques are inadequate for solving these problems Wu (2016); Lu et al. (2023a). Conventional mathematical programming methodologies find themselves inadequately prepared to effectively handle the intricacy and non-linearity inherent in present-day optimization cases Luan et al. (2022); Xiao and Konak (2016). The complex inter-dependencies and high-dimensional spaces encountered in real-world situations frequently result in sub-optimal solutions when employing traditional methods Cao et al. (2019a). In order to surpass these constraints, innovative optimization methodologies, including evolutionary algorithms and metaheuristic methods, have gained prominence due to their capability to traverse intricate solution landscapes and uncover solutions that are nearly optimal Heidari et al. (2022). These advanced techniques utilize stochastic processes and strategies based on population-based search principles, thus solidifying their status as indispensable tools for addressing the diverse and intricate challenges posed by contemporary optimization problems Zhang et al. (2022a); Xu et al. (2023). Stochastic optimization techniques, such as metaheuristics (MHs), have emerged as powerful alternatives Valdez et al. (2017a). MHs are approximation algorithms that find near-optimal solutions within a reasonable computational time Zhang et al. (2022b). They are problem-independent and adaptable to various domains, including image segmentation, feature selection, machine learning optimization, fault diagnosis, economic local dispatch problems, and global optimization, which these works proposed by Zhao et al. (2023); Thaher et al. (2022a,b); ling Chen et al. (2014); Yu et al. (2021); Al-Betar et al. (2022); Wang et al. (2021)

MHs follow a fundamental principle: they generate random solutions or populations and iteratively improve them using stochastic mathematical operators until a termination condition is met Heidari et al. (2017); Zheng et al. (2022); Wang et al. (2023). Among MHs, population-based approaches have gained popularity due to their effective performance Heidari et al. (2019a). These approaches strike a balance between global search (exploration) and local search (exploitation), reducing the effective search space by efficiently exploring promising regions Zhang et al. (2022c). Well-regarded MHs should possess this balance to avoid getting stuck in local optima Boussaïd et al. (2013); Valdez et al. (2017b).

Population-based MHs can be categorized into four major groups based on their inspiration: evolutionary-based, physics-based, human-based, and swarm intelligence (SI) algorithms Mirjalili and Lewis (2016). Examples of these categories include Genetic Algorithms (GA) Holland (1992), Particle Swarm Optimizer (PSO) Tian et al. (2022), Gravitational Search Algorithm (GSA) Rashedi et al. (2009), Teaching Learning Based Optimization (TLBO) Rao et al. (2011), and Whale Optimization Algorithm (WOA) Mirjalili and Lewis (2016). Recently, innovative MHs inspired by nature have emerged, incorporating well-known natural processes into numerical simulations. These algorithms effectively address problems by avoiding local minima, accelerating convergence, and providing accurate solutions Muazu et al. (2022). The Crow Search Algorithm (CSA) is a nature-inspired algorithm that has gained significant attention. It has been successfully applied in various engineering applications, including DNA fragment assembly, image processing, feature selection, power distribution network optimization, and economic load dispatch Hussien et al. (2020); Wang et al. (2022).

The CSA is a nature-inspired, SI-based algorithm that mimics the intelligent foraging behaviors of crows. It was designed by Askarzadeh (2016) after observing the remarkable memory capacity of crows during food search and hiding Askarzadeh (2016). Compared to its competitors, the CSA offers several advantages. It is relatively simple to implement, has a shorter run-time, involves fewer mathematical equations and control settings, and exhibits strong space exploration capabilities Zhao et al. (2023); Qu and Fu (2019). Moreover, it incorporates a built-in control strategy that automatically switches between exploration (diversification) and exploitation (intensification) phases. However, the fundamental CSA algorithm has three major flaws. Firstly, it employs fixed awareness probability and flight length values, limiting its adaptability Necira et al. (2022). Secondly, it adopts a single-mode searching mechanism, where each individual conducts a random search within a sector area defined by its current position, the historical ideal position (memory location) of other individuals, and their value differences. This approach restricts the crow's flying activity, reducing flexibility and mobility Qu and Fu (2019). Thirdly, while the CSA performs well in exploration, it struggles in exploitation. The primary CSA relies on random individuals and probabilities to guide the search process, overlooking the significance of optimal solutions in population evolution. Consequently, the CSA shares flaws common to other swarm intelligence algorithms, such as premature convergence, low search accuracy, and susceptibility to local optima. These issues become particularly challenging in multi-dimensional optimization problems Qu and Fu (2019). To address these shortcomings, researchers have enhanced the CSA by hybridizing it with other optimization techniques, aiming to improve its performance Hussien et al. (2020).

Structured population models, such as the island model, have been proposed to improve the convergence speed and behavior of evolutionary algorithms (EAs) den Heijer and Eiben (2013); Lim (2014). These models partition the population into sub-populations, allowing individuals to cooperate and maintain diversity. Island-based MHs, where each island explores a distinct region of the search space and periodically exchanges information with other islands, have demonstrated excellent performance in solving optimization problems in works proposed by Al-Betar et al. (2017); Abed-alguni et al. (2019); Abed-alguni and Barhoush (2018); Al-Betar and Awadallah (2018); Awadallah et al. (2020); Kushida et al. (2013a); Pais et al. (2014); Thaher and Sartawi (2020); Gozali and Fujimura (2019/03).

In this study, we propose an island-based Enhanced Crow Search Algorithm (iECSA) that combines the advantages of the CSA and the island-based MHs. In summary, our motivation for choosing CSA as our approach was driven by its biological inspiration, the need for addressing CSA's limitations, the continuity of research efforts, the opportunity for comparative analysis, and the desire to enhance both exploration and exploitation capabilities. The iECSA algorithm aims to address the limitations of the CSA by introducing an adaptive tournament selection-based guided mechanism, a multi-mode searching mechanism, and a balanced exploration-exploitation strategy. By incorporating the island model, the iECSA algorithm enhances the search process by maintaining population diversity and utilizing parallel computation. In the following sections, we present the details of the iECSA algorithm and evaluate its performance on various optimization problems.

This paper introduces an enhanced variant of the CSA, called ECSA, which is further reinforced with an island-based model. The proposed island-based ECSA (iECSA) demonstrates superior accuracy and convergence speed when handling various benchmark test sets with real-valued solutions. The contributions of this paper can be summarized as follows:

- To accelerate the convergence speed of the CSA, we introduce an adaptive tournament-based operator that selects the guided solution for each crow. This operator enhances the exploitation potential and introduces additional diversification trends, thereby improving the overall convergence performance.

- We employ a modified random movement operator that takes into account the optimal solution obtained so far, the average position of the population, and a randomly scaled component. This strategy further enhances the exploitation potential and introduces diversification, resulting in improved convergence performance.