Salp Swarm Algorithm

Subjects: Computer Science, Artificial Intelligence

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The Salp Swarm Algorithm (SSA) is a bio-inspired metaheuristic optimization technique that mimics the collective behavior of Salp chains hunting for food in the ocean. While it demonstrates competitive performance on benchmark problems, the SSA faces challenges with slow convergence and getting trapped in local optima like many population-based algorithms.

swarm intelligence | Salp swarm optimizer | global optimization | locally weighted approach

1. Introduction

Machine learning has emerged as a promising solution to automate cardiovascular disease (CVD) risk prediction from electronic health records at a population scale. A variety of supervised algorithms have been explored, including logistic regression, decision trees, support vector machines, naïve Bayes classifiers, and ensemble methods [1]. Among these, ensemble techniques such as random forests and gradient boosting machines have achieved state-of-the-art performance due to their ability to handle complex interactions between risk variables [2]. In particular, extreme gradient boosting (XGBoost) has proven highly effective for medical applications through its efficient implementation of regularized model fitting [3]. Nonetheless, machine learning models remain limited by the improper selection of hyperparameters that determine model complexity, learning, and regularization strategies [4]. Conventional grid searches exhaustively evaluate a fixed set of predefined parameter combinations but scale poorly with dimensions and fail to explore interactions between settings effectively [5]. Random searches offer superior coverage of the search space but evaluate many suboptimal configurations without exploiting promising regions [5]. To address these limitations, metaheuristic techniques have emerged as automated approaches to nonlinear, multimodal hyperparameter optimization problems [6][7][8][9][10]. The class of optimization methods known as metaheuristic algorithms has seen widespread adoption. These methods can be broken down into nine classes, with contributions from fields as varied as biology, physics, sociology, music, chemistry, sports, mathematics, collective behaviors (swarm-based), and hybrid approaches that combine elements from several of these classes [11]. In particular, metaheuristic algorithms are useful for solving high-dimensional, nonlinear, constrained optimization problems that arise in the real world. Metaheuristic algorithms have gained substantial recognition and utilization in diverse fields of research and practical applications. One area where these algorithms have shown promise is in the domain of cardiovascular disease (CVD) risk assessment, a critical healthcare concern worldwide. The use of metaheuristic algorithms in CVD risk assessment presents an opportunity to enhance the accuracy and efficiency of predictive models, enabling healthcare professionals to better identify individuals at high risk of developing cardiovascular diseases. Recent studies have explored the application of metaheuristic algorithms, such as Genetic Algorithms, Particle Swarm Optimization, and Artificial Neural Networks, in developing CVD risk prediction models [12]. These algorithms can effectively process large datasets containing diverse risk factors, biomarkers, and clinical parameters, thereby providing a more comprehensive assessment of an individual's risk profile [13]. The use of these algorithms helps not only with predicting the risk of CVD but also in identifying the key contributing factors and their complex interactions, which can be instrumental in tailoring personalized prevention and treatment strategies [14]. Recent research has also emphasized the importance of integrating data from various sources, including clinical records, medical imaging, and genomic information. Metaheuristic algorithms can aid in fusing these heterogeneous data sources to build more holistic and accurate CVD risk prediction models [15]. Furthermore, considering the rapid advancements in medical technology and the increasing availability of health-related data, the application of metaheuristic algorithms in CVD risk assessment is expected to evolve. This evolution includes the incorporation of deep learning and hybrid models that combine the strengths of different metaheuristic techniques to enhance prediction accuracy and robustness [16].

Bio-inspired swarm intelligence algorithms take inspiration from social behaviors observed in nature to robustly solve complex optimization tasks. The domain of bio-inspired swarm intelligence research is experiencing burgeoning growth, with an increasing number of scholars amalgamating machine learning techniques with optimization algorithms rooted in swarm intelligence in pursuit of enhancing the efficacy and efficiency of machine learning methods [17]. Annually, a plethora of novel swarm intelligence algorithms are introduced with the primary aim of addressing a myriad of optimization problems, including but not limited to Particle Swarm Optimization (PSO), which Kennedy and Eberhart initially introduced [18], or Genetic Algorithms (GAs) [19], Salp Swarm Algorithm (SSA) [20], Artificial Bee Colonies (ABCs) [21], Ant Colony optimization (ACO) [22], differential evolution (DE) [23], and others. Other types that can be listed here include Black Holes (BHs) [24], Thermal Exchange Optimization (TEO) [25], Chemical Reaction Optimization (CRO) [26], etc., all of which are examples of techniques that are based on physics or chemistry. More sophisticated examples include those based on the social behaviors of a human like Teaching–Learning-Based Optimization (TLBO) [27] and Imperialist Competitive Algorithm (ICA) [28], and music-based examples such as Melody Search [29] and Salp Swarm Algorithm (SSA) [20].

The Salp Swarm Algorithm (SSA) constitutes a notable advancement in the realm of bio-inspired swarm intelligence. Developed from the inspiration drawn from the collective behavior of Salps, a type of marine organism, the SSA has garnered considerable attention within the academic community. This algorithm has demonstrated its prowess in addressing complex optimization problems by employing a population of virtual Salps that emulate the biological characteristics and interactions observed in their natural counterparts. The SSA leverages these principles to guide the search process, facilitating the identification of optimal solutions across a spectrum of domains. The algorithm's unique features, including its adaptive mechanisms and its capacity to adapt to dynamic environments, render it a compelling subject of investigation and application within various scientific disciplines [7][30][31][32][33]. Nonetheless, the standard SSA faces some limitations that hinder its search abilities. Like many population-based metaheuristics, the SSA can become stuck in local optima and exhibit slow convergence characteristics [34]. This is due in part to the lack of fine-grained neighborhood information incorporated into Salps' movement updates, which focus exploration more globally without sufficient local refinement [35]. Recent studies have also shown that the SSA's performance degrades for highly multimodal problems with many local optima due to its tendency to converge prematurely to suboptimal solutions [36]. Additionally, the use of fixed control parameters facilitates exploitation but constrains exploration over time, restricting flexibility when tackling diverse problem landscapes [37]. To address these drawbacks, localized adaptations guiding Salps towards high-quality neighboring solutions have been explored as an effective means of balancing exploration and exploitation abilities [35]. To address these drawbacks, in the past few years, multiple modified forms of the SSA have been developed by researchers with the aim of enhancing its performance, rectifying its shortcomings, and augmenting its capabilities.

2. Salp Swarm Algorithm and Its Variants

Algorithms inspired by nature have unique characteristics that have attracted the interest of researchers in many fields, since they may be used for a wide variety of problems. Furthermore, the No Free Lunch Theorem states that there is no silver bullet for optimization problems [38], citing a lack of optimal solutions. Therefore, it is still a challenging task to create novel optimization algorithms suited to the requirements of practical application settings. As a result, there has been a rise in interest in developing new optimization techniques by combining existing, simpler meta-algorithms. Hybridization is gaining popularity because it combines the best features of different algorithms into one, creating new systems with improved efficiency and accuracy. Since its invention in 2017, the Salp Swarm Algorithm (SSA) has been improved iteratively by incorporating many adjustments proposed by researchers. These additions have been carefully selected to strengthen the algorithm's flexibility and efficiency across a wide range of problem-solving domains by catering to specific optimization issues. According to [39], the conventional Salp Swarm Algorithm's (SSA) performance was improved by using the DE algorithm's operators in order to avoid becoming stuck in local optimum solutions and hasten the convergence to the global optimum. The SSAGWO approach was proposed by [31] to adjust the locations of Salp followers using the GWO search strategy. Differential evolution and the SSA are integrated into the proposed study [40] to improve accuracy and convergence rate. El-Shorbagy et al. improved the SSA method to achieve this goal by utilizing a chaotic collection of functions to expand the algorithm's capacity to search across wide regions for the best solutions [41]. QSSALEO [30] presents a novel hybrid that improves the Salp swarm by combining Local Escape Operator (LEO) and Quadratic Interpolation (QI), where the QI technique enhanced the new algorithm's capacity to exploit and the precision of the optimal solution. The LEO was employed on the site of QI of the ideal search element at the same time to solve the local optima problem. The TBLSBCL [32] is a novel search technique that aims to show issues of population diversity, imbalanced exploitation and exploration, and premature convergence in the SSA. The hybridization process includes two stages: The first stage is temporary dynamic fundaments used to represent the hierarchy of followers and leaders in the SSA. This approach raises the number of leaders and decreases the number of followers linearly. The leader's position in the population is also edited using the effective exploitation capabilities of the SSA. The second stage, a competitive learning strategy, is employed to revise the condition of the followers by allowing them to learn from the leading member. Problems with population diversity, unequal exploration and exploitation, and premature convergence are all handled by the one-of-a-kind search strategy known as SSALEO [33]. The SSA has these issues, but SSALEO is able to solve them. The LEO (Local Escape Operator) is the component that contributes to SSALEO by streamlining the search procedure in the Salp Swarm Algorithm and boosting the local search effectiveness of the swarm members. The utilization of the SSA has been widely observed across many applications due to its notable optimization potential. **Table 1** presents a comprehensive compilation of various modifications and hybridizations within the field of the SSA. In the majority of instances, the initial Salp Swarm Algorithm (SSA) was suitably enhanced prior to its implementation. However, it was uncommon for the unmodified SSA to be explicitly implemented. The concept of the No Free Lunch (NFL) theorem effectively exemplifies this notion. This serves as an incentive for academics to participate in the endeavor of enhancing the SSA.

Table 1. SSA modifications and hybridizations.

Approach and Ref.	Methodology	Problems	Limitations of the Approach
ISSA [42]	Several mutation strategies were implemented.	Optimization problems and engineering applications	The phenomenon of slow convergence and the tendency to fall into poor solutions.
ESSA [43]	The incorporation of mutation and crossover procedures into the Salp Swarm Algorithm (SSA) was implemented.	Multi-objective electric power dispatch problem	The phenomenon of premature convergence is a significant concern in the context of multi-objective optimization problems.
CMSRSSSA [44]	The introduction of the composite mutation strategy and the restart mechanism was undertaken.	Optimization problems and engineering applications	The search method exhibits limitations in its effectiveness.
E-SSA [45]	Multiple evolutionary strategies were introduced.	Optimization problems and engineering applications	The convergence pace is relatively low, and there is a need to strike a balance between exploration and exploitation.
WLSSA [46]	The introduction encompassed the incorporation of adaptive weights and the Levy flight mechanism.	Engineering applications	It is often observed that individuals may encounter the challenge of succumbing to local optima, leading to premature convergence.
CSSA [47]	Chaos mutation strategy was introduced.	Optimization problems	The convergence pace is relatively low, and there is a need to strike a balance between exploration and exploitation.
ISSAHF [48]	Combination of SSA with the HHO optimizer.	Optimization problems and engineering applications	The search efficiency is relatively low, making it susceptible to being trapped in local optima.

Approach and Ref.	Methodology	Problems	Limitations of the Approach
CL-SSA [7]	Pairwise competition mechanism was introduced.	Optimization problems and engineering applications	The capacity to balance between exploration and exploitation.
ISSAFD [49]	The introduction of the SCA and disrupt operator was implemented.	Feature selection	The present study examines the phenomenon of local stagnation during the exploratory phase, with a specific focus on the implications of population diversity.
SSA-OBL [50]	Opposition-based learning (OBL) strategy was introduced.	Optimization problems and Engineering applications	The capacity to balance between exploration and exploitation.
OLMSSA [51]	The application of opposition-based learning approaches was employed to enhance.	PV cells parameter extraction	The accuracy is low.
m-SSA [52]	The principles of opposition-based learning and the Levy flight method were introduced.	Engineering applications	Trapped within a suboptimal solution characterized by diminished precision.

significant variety of sponse to n in order to improve the rate of convergence, strike a balance between exploration and exploitation, and steer clear of locally optimal solutions. Moreover, diversity techniques are used in complex optimization algorithms in order to increase search quality and decrease the impacts of genetic drift, which can result in a loss of diversity in bio-inspired algorithms. This is performed in order to maximize the potential of the algorithms.

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