

# A Lévy Flight-Inspired Random Walk Algorithm for Continuous Fitness Landscape Analysis

Yi Wang, Guangdong University of Science and Technology, China\*

Kangshun Li, South China Agricultural University, China

## ABSTRACT

Heuristic algorithms are effective methods for solving complex optimization problems. The optimal algorithm selection for a specific optimization problem is a challenging task. Fitness landscape analysis (FLA) is used to understand the optimization problem's characteristics and help select the optimal algorithm. A random walk algorithm is an essential technique for FLA in continuous search space. However, most currently proposed random walk algorithms suffer from unbalanced sampling points. This article proposes a Lévy flight-based random walk (LRW) algorithm to address this problem. The Lévy flight is used to generate the proposed random walk algorithm's variable step size and direction. Some tests show that the proposed LRW algorithm performs better in the uniformity of sampling points. Besides, the authors analyze the fitness landscape of the CEC2017 benchmark functions using the proposed LRW algorithm. The experimental results indicate that the proposed LRW algorithm can better obtain the structural features of the landscape and has better stability than several other RW algorithms.

## KEYWORDS

Algorithm selection, Fitness landscape analysis, Lévy flight, Random walk algorithm

## 1. INTRODUCTION

Evolutionary algorithms guided by heuristic principles have demonstrated their prowess in effectively addressing a multitude of real-world challenges (Zolpakar et al., 2021). In this dynamic landscape, the performance of diverse algorithms across distinct optimization problems exhibits notable variation. It is evident that a universal algorithmic solution capable of efficiently tackling all optimization problems remains an elusive aspiration (Singh et al., 2021). Regrettably, the present landscape of evolutionary algorithm research often overlooks the vital interplay between the specific optimization problem and the algorithmic approach adopted. Nevertheless, a promising avenue emerges through the analysis of an optimization problem's fitness landscape, serving as a valuable compass in the design and tailoring of evolutionary algorithms (Lu et al., 2019).

DOI: 10.4018/IJCNIN.330535

\*Corresponding Author

This article published as an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>) which permits unrestricted use, distribution, and production in any medium, provided the author of the original work and original publication source are properly credited.

A fitness landscape takes form by compiling fitness values within the solution space, as highlighted by (Fragata et al. 2019). The tool of choice for unearthing the intricacies of optimization problems, Fitness Landscape Analysis (FLA), discerns essential attributes like entropy, neutrality, and smoothness. Scholars have been keenly focused on integrating FLA methodologies into evolutionary algorithms (Li et al., 2020). The exploration of landscape topologies has been pursued through various metrics, as evidenced by Malan et al.'s three-pronged approach (Malan et al., 2013). Similarly, Sallam et al. delved into landscape insights concerning diverse Differential Evolution (DE) operator selections (Sallam et al., 2017). Li et al. introduced dynamic fitness landscape analysis techniques to understand optimization problems comprehensively. Additionally, landscape characteristics are useful in assessing DE performance (Li et al., 2019). Among notable contributions, Huang et al. conceived a multi-objective differential evolution, titled Landscape Ruggedness Multi-Objective Differential Evolution (LRMODE), wherein information entropy informed the landscape's structural examination, steering DE's strategy selection (Huang et al., 2020). Tan et al.'s Fitness Landscape-Based Differential Evolution (FLDE) stands out, leveraging fitness landscape features to train the K-nearest neighbors (KNN) algorithm. This approach aptly guides mutation strategy selection based on distinct optimization problems (Tan et al., 2021). Within this literature, the exploration of landscape topologies chiefly centers on dissecting the sample points gleaned from a random walk. Methods such as auto-correlation coefficients, entropic measures, and dispersion metrics have been explored in the context of simple random sampling, extracting pivotal landscape attributes tied to optimization problems (Lang et al., 2019).

A random walk (RW) is a technique employed in various fields, beginning from an initial point in the defined space, creating neighboring points through a mutation operator based on the initial point, selecting the next point randomly from these neighbors, and subsequently generating a new set of neighborhood points based on the chosen point. This process continues iteratively. An illustrative example includes the work of Flyvbjerg et al. (1992), who introduced a straightforward random walk (SRW) algorithm for landscape analysis. Expanding on this concept, Malan et al. (2014) introduced the progressive random walk (PRW) algorithm, which involves multiple walks to sample neighborhood structures in continuous space. Another approach Jana et al. (2018) proposed is the chaos-based random walk (CRW) algorithm, which leverages chaotic mappings to generate random numbers and gain insights into local landscape features. However, it's important to note that the uniformity of sampling within the search space of a random walk algorithm significantly relies on the chosen sampling points. Consequently, the significance of RW algorithms or sampling methods is closely tied to landscape analysis (FLA), which offers valuable insights into the structural characteristics of the search space (Lang et al. 2020).

This paper introduces an innovative Lévy flight-based random walk (LRW) algorithm designed to extract essential fitness landscape features within a continuous search space. In the LRW approach, the Lévy flight mechanism governs both the step size and the directional changes of the random walk. The subsequent position of the walk is determined by the product of a random number and the adjustable step size. The LRW algorithm is compared against three other RW algorithms through a series of experiments to validate its effectiveness. Additionally, the proposed LRW algorithm is applied to analyze the landscape characteristics of the CEC2017 function set. The comprehensive experimental results unequivocally demonstrate the superior performance of the LRW algorithm in comparison to the other three RW algorithms.

The subsequent content of this paper is outlined as follows: In Section 2, we explore the simple random walk algorithm. Section 3 delves into an insightful discussion of several techniques tailored to analyze fitness landscapes. Transitioning to Section 4, we unveil the meticulously crafted framework underpinning our novel algorithm. The empirical findings and ensuing discussions are revealed in Section 5, shedding light on the experimental results. Summarizing the culmination of our study, Section 6 encapsulates the key takeaways and presents a prospective outlook on potential avenues for future research.

16 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: [www.igi-global.com/article/a-lvy-flight-inspired-random-walk-algorithm-for-continuous-fitness-landscape-analysis/330535](http://www.igi-global.com/article/a-lvy-flight-inspired-random-walk-algorithm-for-continuous-fitness-landscape-analysis/330535)

## Related Content

---

### A Fresh Look at Graphical Web Browser Revisitation using an Organic Bookmark Management System

Siu-Tsen Shen and Stephen D. Prior (2012). *Cognitively Informed Intelligent Interfaces: Systems Design and Development* (pp. 41-55).

[www.irma-international.org/chapter/fresh-look-graphical-web-browser/66266](http://www.irma-international.org/chapter/fresh-look-graphical-web-browser/66266)

### Balancing Exploration and Exploitation With Decomposition-Based Dynamic Multi-Objective Evolutionary Algorithm

Qing Zhang, Ruwang Jiao, Sanyou Zeng and Zhigao Zeng (2021). *International Journal of Cognitive Informatics and Natural Intelligence* (pp. 1-23).

[www.irma-international.org/article/balancing-exploration-and-exploitation-with-decomposition-based-dynamic-multi-objective-evolutionary-algorithm/273135](http://www.irma-international.org/article/balancing-exploration-and-exploitation-with-decomposition-based-dynamic-multi-objective-evolutionary-algorithm/273135)

### Modeling Self-Efficacy as a Dynamic Cognitive Process with the Computational-Unified Learning Model (C-ULM): Implications for Cognitive Informatics and Cognitive Computing

Duane F. Shell, Leen-Kiat Soh and Vlad Chiriacescu (2015). *International Journal of Cognitive Informatics and Natural Intelligence* (pp. 1-24).

[www.irma-international.org/article/modeling-self-efficacy-as-a-dynamic-cognitive-process-with-the-computational-unified-learning-model-c-ulm/140684](http://www.irma-international.org/article/modeling-self-efficacy-as-a-dynamic-cognitive-process-with-the-computational-unified-learning-model-c-ulm/140684)

### Constructivist Learning During Software Development

Václav Rajlich and Shaochun Xu (2007). *International Journal of Cognitive Informatics and Natural Intelligence* (pp. 78-101).

[www.irma-international.org/article/constructivist-learning-during-software-development/1542](http://www.irma-international.org/article/constructivist-learning-during-software-development/1542)

### Dimensional Music Emotion Recognition by Machine Learning

Junjie Bai, Lixiao Feng, Jun Peng, Jinliang Shi, Kan Luo, Zuojin Li, Lu Liao and Yingxu Wang (2016). *International Journal of Cognitive Informatics and Natural Intelligence* (pp. 74-89).

[www.irma-international.org/article/dimensional-music-emotion-recognition-by-machine-learning/172534](http://www.irma-international.org/article/dimensional-music-emotion-recognition-by-machine-learning/172534)