A Physarum-Inspired Competition Algorithm for Solving Discrete Multi-Objective Optimization Problems

Abubakr Awad
Department of Computing Science,
University of Aberdeen
Aberdeen, UK
abubakr.awad@abdn.ac.uk

Muhammad Usman
Department of Computing Science,
University of Aberdeen
Aberdeen, UK
m.usman.17@abdn.ac.uk

David Lusseau
Institute of Biological and
Environmental Sciences, University of
Aberdeen
Aberdeen, UK
d.lusseau@abdn.ac.uk

George M. Coghill
Department of Computing Science,
University of Aberdeen
Aberdeen, UK
g.coghill@abdn.ac.uk

Wei Pang
Department of Computing Science,
University of Aberdeen
Aberdeen, UK
pang.wei@abdn.ac.uk

ABSTRACT

Many real-world problems can be naturally formulated as discrete multi-objective optimization (DMOO) problems. In this research we propose a novel bio-inspired Physarum competition algorithm (PCA) to tackle DMOO problems by modelling the Physarum discrete motility over a hexagonal cellular automaton. Our algorithm is based on the chemo-attraction forces towards food resources (Objective Functions) and the repulsion negative forces between the competing Physarum. Numerical experimental work clearly demonstrated that our PCA algorithm had the best performance for the spread indicator against three state-of-the-art evolutionary algorithms, and its effectiveness in terms of commonly used metrics. These results have indicated the superiority of PCA in exploring the search space and keeping diversity, this makes PCA a promising algorithm for solving DMOO problems.

CCS CONCEPTS

• **Theory of computation → Discrete optimization**; • **Computing methodologies → Bio-inspired approaches**.

KEYWORDS

Physarum, Competition, DMOO, 2D Hexagonal grid, Diffusion

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1 INTRODUCTION

Most of the existing research has focused on continuous MOO problems [8]. However, many practical problems can be naturally formulated as discrete multi-objective optimization (DMOO) problems and is considered more challenging [4]. Slime mould (Physarum) may not have brains, but they are capable of solving many NP hard problems [7].

A major problem with many swarm intelligence algorithms is rapid premature convergence as they focus on social collaboration within the population, and they seldom concentrate on the competitions among individuals [1]. In this research, we aim to explore the potential of individual skills of competing Physarum to achieve efficient exploration of the search space, keeping diversity of solutions and to increase the ability of escaping from local optima.

2 PHYSARUM-INSPIRED COMPETITION ALGORITHM

We have proposed a novel bio-inspired Physarum competition algorithm (PCA) to solve DMOO problems by modelling the Physarum motility over a two dimensional hexagonal cellular automaton that allows discrete and effective search (Algorithm 1). Each cell in the grid will be decoded as a solution and will be regarded as a food resource. In the exploration phase, the competing Physarum will explore the search space according to diffusion equation [6] based on the chemo-attraction forces towards food resources and the repulsion negative forces that competing Physarum exert on each other. In the Physarum exploitation phase, the protoplasmic flux connected to high quality food resources (non-dominated solutions) tend to increase, while the protoplasmic flux to poor quality food resources (dominated solutions) tend to decrease as a feedback mechanism [5].

3 EXPERIMENTAL STUDY

We have implemented our PCA in Java and integrated it with jMetal (multi-objective optimization framework) [3] to assess the performance of our PCA versus three state of-the-art evolutionary algorithms as Non-dominated Sorting Genetic Algorithm (NSGAII), (NSGAIII), and Strength Pareto Evolutionary Algorithm (SPEA2).

Algorithm 1: PCA for solving DMOO

$GPF = \{\}$; // Initialize empty global Pareto front
/* Initialize Physarum (solutions) $\{S = P_1, P_2, \ldots, P_{np}\}$ */
foreach *Physarum* (P_i) **do**
  $P_i.mass \leftarrow init\_pm$ // Initialize Physarum mass
  $P_i.lpf \leftarrow \{\}$ // Initialize empty local Pareto front for Physarum
  Randomly place Physarum (position vector) P_i in the search space.
end
current-iter = 0
while *current-iter* < *max-iter* **do**
  foreach *Physarum* (P_i) **do**
    Add Physarum P_i (solution) to it's *LPF* (If not dominated by other solutions in Physarum *LPF*)
    // Initialize Physarum Neighbourhood
    foreach *Cell* c_k *in Physarum* P_i *Neighbourhood* **do**
      if *Physarum* (P_i) *can diffuse to cell* (c_k) **then**
        Add a new Physarum (P_k) to the search space with initial mass 0
      end
    end
  end
  foreach *Physarum* (P_i) **do**
    Diffuse P_i^t to the neighbouring cells.
  end
  current-iter = *current-iter* + 1
end
Compute *GPF* from each Physarum *LPF*.

Hypervolume (HV), Inverted Generational Distance Plus (IGD+), Epsilon and Spread were used as indicators for performance. Deep valley bi-objective optimization problem was selected as its continuous counterpart MOO problem is considered to be difficult for evolutionary population based algorithms [2]. The feasible set of this problem is the integer points within the square $[0, 100] \times [0, 100]$, and the Pareto front is located at the bottom of a deep valley from the dominated regions. To avoid statistical inferences, 40 independent runs were executed. Further, Kruskal-Wallis non-parametric test and pair-wise analysis were used to compare the performance between different algorithms.

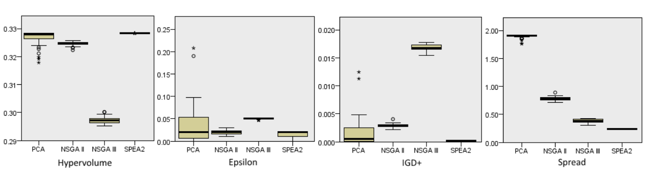

Figure 1: Box-Plot graph of performance indicators in Deep Valley problem.

Table 1: The statistical pair-wise analysis of performance indicators in Deep Valley problem.

	HV	Epsilon	IGD+	Spread
PCA - NSGAII (Sig.)	▲ (0.040)	− (1.000)	▲ (0.005)	▲ (0.001)
PCA - NSGAIII (Sig.)	▲ (0.001)	▲ (0.001)	▲ (0.001)	▲ (0.001)
PCA - SPEA2 (Sig.)	▽ (0.001)	▽ (0.008)	− (0.087)	▲ (0.001)

The box plots and pairwise analysis of all indicators showed that our algorithm had the best performance for the spread indicator, and the second best values for the IGD+, the HV and Epsilon indicators only exceeded by SPEA2 (Figure 1 and Table 1). These results analysis clearly demonstrated the ability of our algorithm to provide a better spread of solutions with good convergence behaviour. This has confirmed our assumption that individual skills of competing Physarum are more efficient in exploration, which increases the diversity of solution.

4 CONCLUSION AND FUTURE WORK

The PCA algorithm has achieved similar performance compared to the state-of-the-art EMO algorithm SPEA2, and it even outperformed others like NSGAII and NSGAIII. All the above suggests that PCA is a promising algorithm for solving DMOO problems, and we envision that many improvements can be made to achieve better performance.

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