Ant Swarm Algorithm for Self-Organizing Complex System

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ABSTRACT

This paper proposes a methodology to analyze complex systems' self-organizing characteristics by utilizing a double-layer ant swarm algorithm. The basic components comprising a complex system are defined as interacting nodes, and each node hosts multiple ants, which motions represent possible traces of the corresponding node. A representative group-state for the entire complex system is formed by randomly selecting one ant from all nodes. The methodology further proposes constructing a fitness function to guide the random ant-group moving with reduced entropy generation at the system level. Simultaneously, ants within a single node move by pheromone-based coordination. The proposed methodology is used to analyze Abelian Sandpile Model (ASM). Two types of coordinating algorithms, stochastic greedy and chaotic, are constructed to evaluate the methodologies' robustness. The results demonstrate that both coordinating algorithms can successfully capture ASM's collective characteristics, such as average sandpile height and recursive rates for different heights, although these two algorithms represent different searching dynamics.

CCS CONCEPTS

• **Theory of computation → Evolutionary algorithms**; **Self-organization**.

KEYWORDS

Swarm Intelligence, Self-Organizing Criticality, Complex System, Thermodynamic Processes, Abelian Sandpile Model, Entropy Production, Chaotic Ant Swarm

ACM Reference Format:
Juntao Zhang and Peng Cheng. 2021. Ant Swarm Algorithm for Self-Organizing Complex System. In *2021 Genetic and Evolutionary Computation Conference Companion (GECCO '21 Companion), July 10–14, 2021, Lille, France.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3449726.3459502

1 INTRODUCTION

Agent-based models have demonstrated remarkable efficacy in analyzing complex systems' collective behaviors. However, few developed algorithms are mature or widely adaptive to different application scenarios [9]. This paper proposes a methodology to construct a double-layer ant swarm for complex systems that considers both local information exchange among ant agents and the entire community's influence on the individual ant. The so-called double-layer swarm includes a node layer (macro-scale) and a sub-swarm layer (micro-scale). Figure 1 schematically illustrates the structure of the proposed double-layer ant swarm. Multiple swarm agents (i.e., ants) are assigned to a single node, that each agent represents a possible state for the node. Only agents assigned to the same node can be neighbors, in which sense every node contains a sub-swarm de facto.

One agent is randomly selected at each iteration from each node to form a representative set, which stands for a possible macrostate for the entire system. A fitness function applies to this temporary set and achieves the corresponding entropy information. This fitness function guides the ants moving along the direction that lowers the whole system's entropy production, similar to Artificial Potential Function (APF), but no velocity information is needed. This method utilizes the ideas proposed by Prigogine [8] and Kugler & Turvey [6] that self-organizing could be the result of the competitions among several disorder procedures coupled to a multi-agent system (MAS), and it represents the equilibrium state with maximum system entropy or minimal entropy production (i.e., entropy variation rate). Within this double-layer structure, the fitness function coordinates interactions among nodes (macro-scale), but pheromone-based coordination only works within the sub-swarm (micro-scale). To verify the proposed methodology's effectiveness,

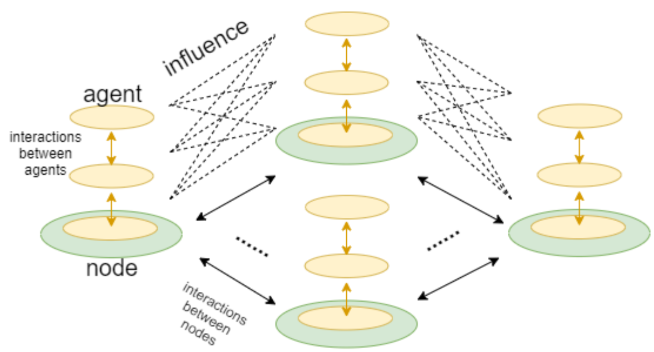

Figure 1: Schematic structure of the double-layer ant swarm.

we select Abelian Sandpile Model (ASM) as the exemplary case. A stochastic greedy algorithm with discrete state space and a chaotic algorithm with continuous state space are constructed under the double-layer swarm framework. The results and corresponding comparisons can provide insight into the essential mechanism utilized to capture the emergence of self-organizing characteristics.

ACM ISBN 978-1-4503-8351-6/21/07.
https://doi.org/10.1145/3449726.3459502

2 ALGORITHMS FOR ASM

A classical 2D ASM of size $M \times M$ is a simple self-organizing complex system with its collective behavior fully analytical and tractable [2, 3, 7]. There are four possible grain heights at each site of the $M \times M$ lattice, i.e., $s \in \{0, 1, 2, 3\}$. The threshold h_c is 4, beyond which a topple would occur, throwing out grains from this site. An ant swarm of size N (i.e., there are N ants in total) is uniformly assigned to the $M \times M$ sandpile ($M \times M$ nodes in total), that each node has l_{asgn} ants and $N = M^2 l_{asgn}$. The state at each site is discrete and finite, i.e., $s \in \{0, 1, 2, 3\}$. States on all sites form the space $\mathbf{S}$. The state at each site is denoted as $s_{(i,j)}$ and a set $A = \left\{s_{(i,j)} \middle| i = 1, 2, \ldots, M; j = 1, 2, \ldots, M\right\}$ represents a possible configuration of the sandpile system. The position of the k^{th} ant, which belongs to the lattice (i, j), can be represented as $p_k = s_{(i,j)}$, and accordingly $h(i, j) = p_k$.

In the discreet Stochastic Greedy Algorithm (SGA), there are four parameters involved in the iteration for each ant: position p_k for k^{th} ant, where $k = 1, \ldots, N$; trail possibility $tr_{k,s}$ for k^{th} ant moving to s, where $s \in \{0, 1, 2, 3\}$, and $\sum_{s=0}^{3} tr_{k,s} = 1$;pheromone $\varphi_{k,s}$ for k^{th} ant at s, where $s \in \{0, 1, 2, 3\}$ and $tr_{k,s} = \frac{\varphi_{k,s}}{\sum_{s=0}^{3} \varphi_{k,s}}$.

At the beginning the iteration, the entire ant swarm will be initialized with random positions and all pheromone value is set to the same positive constant C, i.e., $\varphi_{k,s} = C > 0$. Then a representative set A^* is formed by randomly selecting one ant from every node. $A^* = \left\{h^*_{(i,j)} \middle| i = 1, 2, \ldots, M; j = 1, 2, \ldots, M\right\}$, and $h^*_{(i,j)} = p_{k^*}$, where k^* is not a consecutive number serie.Dropping a sand grain on a random site on A^* will cause the local height to rise by 1 or trigger toppling, which induces enthalpy and entropy changes to the system. Two fitness functions are built to measure this change, representing different observations:

$$F_1(k) = sa(i, j) \tag{1}$$

$$F_2(k) = (Sa + 1) \times \frac{\left|h_{k,t} - h_{k,t+1}\right|}{h_c} \tag{2}$$

where Sa is the avalanche scale for the toppling event, that:

$$\begin{cases} sa = 0, \text{ if no toppling at site } (i, j) \\ sa = \text{size of avalanche, if toppling triggered at site} (i, j) \end{cases} \tag{3}$$

Within site (i, j), the best position is determined by the ant having the largest F_1 (or F_2) value. The ants at site (i, j) are denoted by $k(i, j)$, the ant with the largest F_1 is $k_b(i, j)$, and its position is $s[k_b(i, j)]$. All ants assigned to this node will have their pheromone updated by:

$$\varphi_{k(i,j), s[k_b(i,j)]} = F_1\big(k_b(i, j)\big) \tag{4}$$

Equation 4 will change the trail probability of all ants within the same node. Moreover, between iteration steps, t and $t + 1$, the pheromone will evaporate by:

$$\varphi_{k,s}(t + 1) = (1 - \rho)\varphi_{k,s}(t) \tag{5}$$

A double-layer ant swarm based on continuous space is further built by utilizing the Chaotic Ant Swarm (CAS) algorithm developed by Li et al. [4, 5]. In this algorithm, s is relaxed to a continuous real number range, i.e., $s \in [0, 4)$, that a state larger than 3 is allowed in the model, attempting to free the ants' searching space around 3.

Table 1: Hight Distribution for Experiments

	P_0	P_1	P_2	P_3
Analytical Value	7.40%	17.40%	30.60%	44.60%
SGA+F_1	7.87%	15.34%	27.31%	49.48%
SGA+F_2	8.19%	14.56%	26.69%	50.56%
CAS+F_2	4.6%	17.9%	34.3%	43.1%

Similar behavior equations for ants as in [4, 5] are adopted and F_2 is the fitness function.

3 RESULTS AND CONCLUSIONS

Developed algorithms evaluate sandpile's average height and distribution of the four heights and get an excellent match to the analytical results. For a 121x121 sandpile, SGA achieves an average height of 2.17 with F_1 and 2.19 with F_2. CAS with F_2 gets an average height of 2.12. The analytical value is 2.125. Table 1 lists the distribution of the four heights. It is found that SGA intends to over-estimate the occurrence of height 3, and F_2 with additional observable involved for entropy elongates the convergence but has negligible impacts on the results. CAS' results are slightly better than SGA's, and more statistical information regarding the self-organizing sandpile can be retrieved. The results demonstrate the proposed double-layer ant swarm is open to different mathematical schemes for both the macro-scale (node layer) and micro-scale (sub-swarm layer) coordinations. This paper proposes an energy-related enthalpy concept as an approximation of entropy while constructing the fitness function. The comparison between two different fitness functions demonstrates the robustness of the proposed methodology, which is crucial to real systems applications. A good example is a self-organizing thermodynamic system (SOTS) [1] that utilizes two-phase fluid and heat flow in an interconnected microchannel network as a passive heat transfer device for electronic systems. Preliminary results have verified the effectiveness of the algorithm. Complete investigations are planned in the short future.

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