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On Extremal optimization in Honey Bee Foraging

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Abstract

Bee foraging is an efficient operation done by the honeybees. Trying to understand it is an important problem. Here we use extremal optimization to model it.

Keywords: Bee foraging; Nectar loads; Coherent colony level; Extremal optimization; Annihilation probability; Clone; Monotonically in time; Bulk; Long-time memory; Energy efficiency; Monotonic; Random element

Abbreviations: EO: Extremal optimization; IS: Immune System; SOCO: Single Objective Combinatorial Optimization

Introduction

In Bee foraging neither do the foragers compare different nectar sources to determine the relative profitability of any one source, nor do the food stores compare different nectar loads and indicate the relative profitability of each load to the foragers [1]. Instead, each forager knows only about its particular nectar source and independently calculates the absolute profitability of its source. Even though each of a colony's foragers operates with extremely limited information about the colony's food sources, together they will generate a coherent colony level response to different food sources in which better ones are heavily exploited and poorer ones are abandoned. This is similar to the idea of extremal optimization [2].

Extremal optimization

Extremal optimization (EO) is a metaheuristic method which is quite similar to the way the immune system (IS) renews its cells [3]. Almost every day new immune cells are replaced in the blood stream. If within few weeks they were able to recognize antigens (viruses or bacteria) then they are preserved for longer period. Otherwise they are replaced randomly. This dynamic is called extremal dynamics [4]. It can explain the long-range memory of the immune system even without the persistence of antigens. The reason is that if a system evolves according to such dynamics then the annihilation probability for a clone (a type of cells) that has already survived for time t is proportional to $1/(1+tc)$ where c is a constant. Boettcher and Percus has used EO to solve some single objective combinatorial optimization problems (SOCO) [4].

Definition 3

Extremally driven systems are the systems that updated by identifying an active region of the system and renewing this region whilst leaving the remainder unchanged. The active subsystem is chosen according to some kind of extremal criterion; often it is centered on the location of the minimum of some spatially varying scalar variable.

Consider a system of N elements, each element assigned a single scalar variable $x(i)$, $i=1,2,\ldots,N$ drawn from the fixed probability distribution function $p(x)$. For every time step, the element with the smallest value in the system is selected and renewed by assigning a new value which is drawn from $p(x)$. It is assumed that no two $x(i)$ can take the same value.

Definition 4

For the above system the typical values of $x(i)$ increase monotonically in time. This means that any renewed element is likely to have a smaller $x(i)$ than the bulk, and hence a shorter than average lifespan until it is again renewed. Corresponding, elements that have not been renewed for some time will have a longer than average life expectancy. This separation between the shortest and the longest-lived elements will become more pronounced as the system evolves and the average $x(i)$ in the bulk increases. This phenomenon is called long-time memory.

Proposition 2

Extremally driven systems can generally be expected to exhibit long-term memory [4].

Proposed algorithm

i. Every site i has a fitness $f(i)=e(i)/n(i)$ where $e(i)$ is energy efficiency (energy gained per energy spent) from it and $n(i)$ is number of foragers using it.

ii. If $f(i)>=rnd$, where rnd is a random number uniformally distributed between [0,1], then $n(i)$ remain the same.

iii. If $f(i)>=rnd$, then choose an integer j randomly such that $f(j)>rnd$ then $n(i)=n(i)-1$ and $n(j)=n(j)+1$.

We have simulated this algorithm and obtained the following result:

f	.070	.228	1	1	1	1	1	1	1	1
n	0	0	1	1	2	3	4	4	4	4

Although the result is mainly monotonic but some deviations are expected due to the random element of the process.

Our results agree with the results of [5].

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