Session: Bacterial Foraging Algorithm

Course Title: Computational Intelligence
Course Code: 19MIE501A

Course Leader:
Dr. Vaishali R. Kulkarni
Assistant Professor, Department of Computer Science and Engineering
Faculty of Engineering and Technology
Ramaiah University of Applied Sciences, Bengaluru
Email: vaishali.cs.et@msruas.ac.in
Tel: +91-804-906-5555 Ext:2222
Website: http://www.msruas.ac.in/staff/fet$_c$*seVaishali*

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4. Chemotaxis, elimination and dispersal and reproduction in E. Coli bacteria
5. The bacterial foraging optimization; and algorithm and all its important parameters

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4. Implement Bacterial Foraging Optimization (BFO) Algorithm to solve a continuous optimization problem
5. Choose proper values of algorithm parameters based on the nature of the problem at hand

Recommended Resources for this Session

1. K. M. Passino. (2002). "Biomimicry of bacterial foraging for distributed optimization and control". IEEE Control Systems Journal. volume 22, number 3, pp. 52–67.

2. Kulkarni R. V. and Venayagamoorthy, G. K. (2010). "Bio-inspired algorithms for autonomous deployment and localization of sensor nodes." *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, issue 6, volume 40, pp. 663–675.

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- Animals having successful foraging skills are more likely to enjoy reproductive success
- This evolutionary principle has inspired scientists in “foraging theory” to model foraging as an optimization process
- An animal attempts to maximize the energy obtained per unit time spent foraging, under the constraints of its own physiology (e.g., sensing and cognitive capabilities) and environment (e.g., density of prey, risks from predators, physical characteristics of the search area)

Elements of Foraging Theory

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- Patches are encountered sequentially, and great effort and risk are needed to travel from one patch to another

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- Optimal foraging theory formulates the foraging as an optimization problem and via computational or analytical methods can provide an optimal foraging policy that specifies how foraging decisions are made

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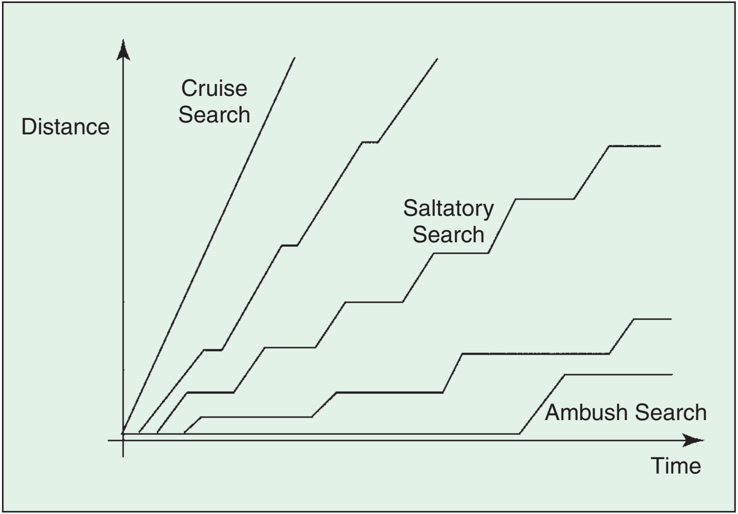
- Researchers have shown that foraging decision heuristics are used very effectively by animals to approximate optimal policies

Search Strategies for Foraging Animals



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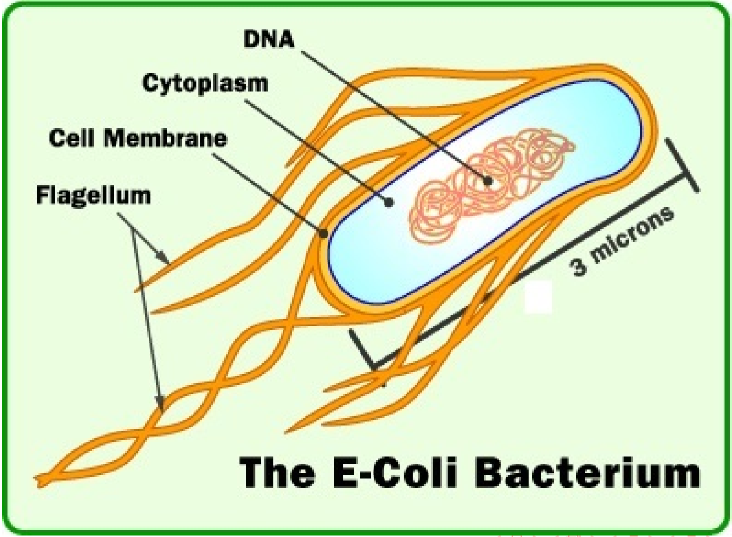
- Even extremely simple organisms like Bacteria can still work together for the benefit of the group

Escherichia Coli (E. coli) Bacterium



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- It swims away from alkaline and acidic environments and toward more neutral ones

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- After a tumble, the cell is pointed in a **random** direction

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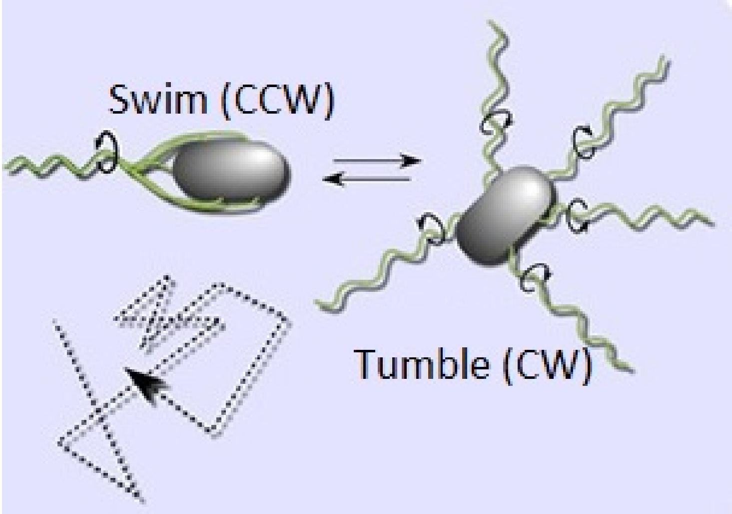

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- When it reaches constant nutrient concentration, it returns to baseline behavior. It is never satisfied with the amount of surrounding food; it always seeks higher concentrations

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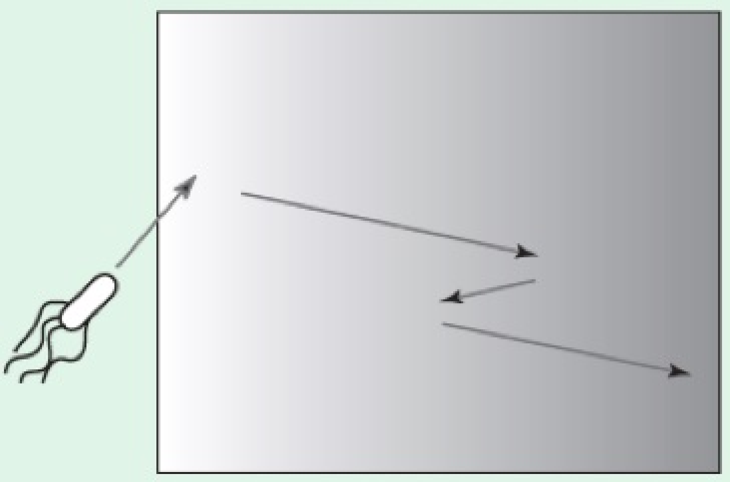

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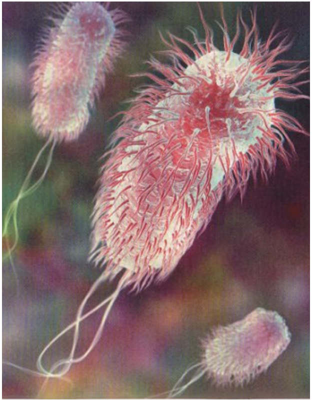
- Elimination and dispersal are parts of the population-level long-distance motile behavior

Bacterial Foraging Optimization Algorithm (BFOA)



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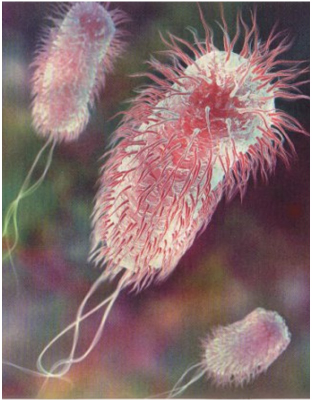

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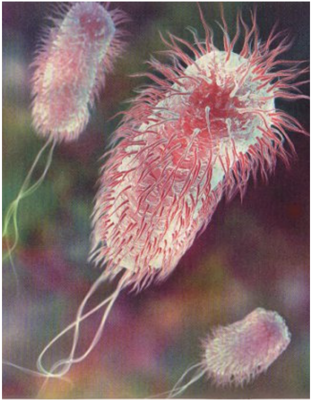

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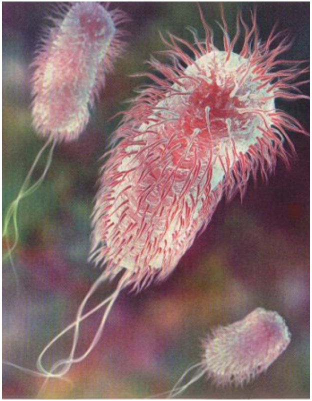

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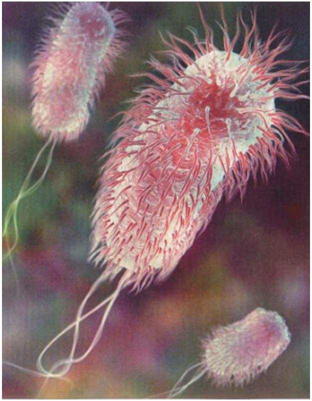

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- It contains a colony of candidate solutions called **bacteria** that move in an n-dimensional search space
- Each bacterium moves using two types of movements: swimming and tumbling
- The goal is to achieve better fitness in a way similar to natural bacteria that thrive to move to higher concentration of nutrients

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- This swimming is continued until a minimum fitness value is reached, but only for a maximum number of steps N_s
- After N_c chemotactic steps, a reproduction step is taken, in which the population is sorted in ascending order of the objective function value J and the least healthy bacteria are replaced by the copies of the healthier bacteria

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- After N_{re} reproduction steps, an elimination-dispersal step is taken
- Here, a bacterium is eliminated and a new bacterium is created at a random location in the search space with probability p_{ed}
- The optimization stops after N_{ed} elimination-dispersal rounds

Swarming in BFOA

- Bacteria create swarms by means of cell-to-cell signalling via an attractant and a repellent. Cell-to-cell attraction for bacterium i is represented with $J_{cc}(\mathscr{P}, P_i), i = 1, 2, \cdots, S$

$$
\begin{aligned}
J_{cc}(\mathscr{P}, P_i) = & \sum_{t=1}^{S} \left[-d_a exp \left(-w_a \sum_{m=1}^{p} (P_{i,m} - P_{t,m})^2 \right) \right] \\
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- Here, $J_{cc}(P_i, \mathscr{P})$ denotes the combined cell-to-cell attraction and repulsion effects for bacterium i at position $P_i = [P_{i,1}, P_{i,2}, \cdots, P_{i,p}]^T$ and the whole swarm of bacteria $\mathscr{P} = \{P_1, P_2, \cdots, P_S\}$

Guidelines on BFOA Parameters

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- A general biologically inspired rule of thumb for choosing the parameters of BFOA is: $N_c > N_{re} > N_{ed}$

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5. Important parameters: Numbers of elimination and dispersion rounds, reproduction rounds, chemotaxis rounds, swimming rounds

Any Questions?

Thank You