Biomimicry of Bacterial Foraging
for Distributed Optimization and Control

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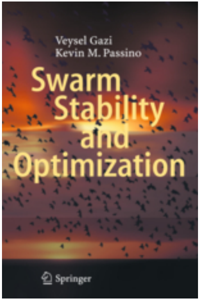
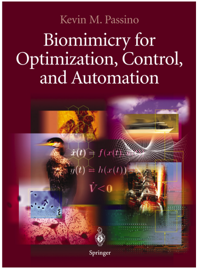
About the Author





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Foraging

Foraging

- searching for nutrients
- avoiding noxious stimuli (toxins, predators, etc)

Social Foraging

- increases likelihood of finding nutrients
- better detection and protection from noxious stimuli
- gains can offset cost of food competition

Foraging as Optimization

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  - smaller values of J = more nutrients, less noxious stimuli
  - higher values of J = more noxious stimuli, less nutrients

Foraging as Optimization

How can we view foraging as an Optimization Process?

- We have some parameters θ and a loss function $J(\theta)$ that we want to minimize
- θ can represent the position of an organism in its environment
- J can represent the concentration of nutrients and noxious stimuli
  - smaller values of J = more nutrients, less noxious stimuli
  - higher values of J = more noxious stimuli, less nutrients
- In general, J and θ can be arbitrary
  - $\theta \in \mathbb{R}^p$
  - $J : \mathbb{R}^p \to \mathbb{R}$

E. coli

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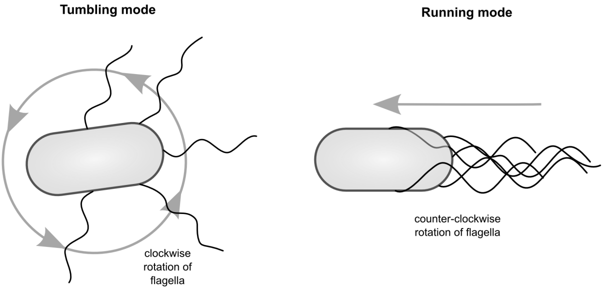
- Social organism
  - Secretes signals to attract others nearby
  - Encourages "swarming" or "clumping"

E. coli Behaviour

- Swims using left-handed helical flagella ("propellers")
  - **Tumble**: flagella all rotate clockwise → pull on cell in all directions → random movement
  - **Run**: flagella all rotate counterclockwise → flagella form a bundle → push on cell in one direction → directed movement



E. coli Behaviour

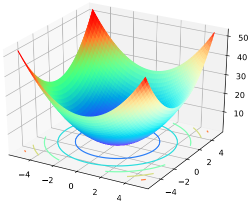
- If during a tumble *E. coli* swims down a nutrient concentration gradient:
  - Prolongs time spent on a run
  - Continues moving in the same direction
- Otherwise:
  - Tends to switch to a tumble (search for more)
  - Moves randomly which searching for more nutrient gradients to exploit
- Call a tumble followed by a run a "chemotaxis step"

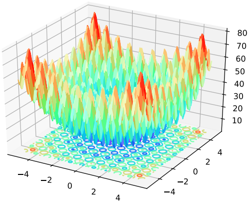
Algorithm for a Single Bacterium

for $j \leftarrow 1 \dots N_c$ **do**:
  $\phi \sim \mathcal{U}$
  $\theta \leftarrow \theta + c\phi$
  while $J(\theta + c\phi) < J(\theta)$ **do**:
    $\theta \leftarrow \theta + c\phi$

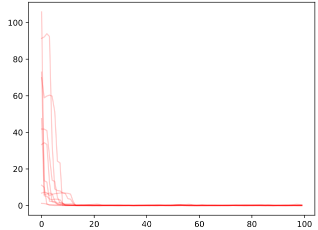
- θ: p-dimensional vector (randomly initialized)
- N_c: number of chemotaxis steps
- $\phi \sim \mathcal{U}$: a random unit vector
- c: a step-size

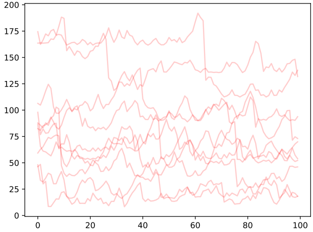
Loss Function to Optimize

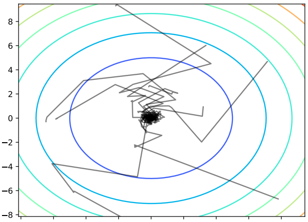


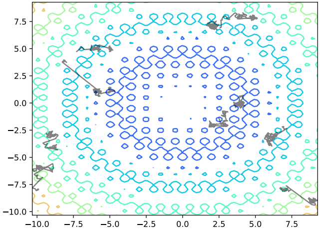


Results of Single Bacterium









Algorithm for a Colony

for $j \leftarrow 1 \ldots N_c$ **do**:
  for $i \leftarrow 1 \ldots S$ **do**:
    $\phi \sim \mathcal{U}$
    $\theta_i \leftarrow \theta_i + c_i \phi$
    while $J(\theta_i + c_i\phi) + J_{cc}(\theta_i + c_i\phi) < J(\theta_i) + J_{cc}(\theta_i)$ **do**:
      $\theta_i \leftarrow \theta_i + c_i \phi$

- θ_i: ith p-dimensional vector (randomly initialized)
- N_c: number of chemotaxis steps
- S: number of bacteria in the colony
- $\phi \sim \mathcal{U}$: a random unit vector
- c: a step-size for bacterium i

J_{cc} and swarming behaviour

- *E. coli* do social foraging
- Secrete a substance to indicate to attract nearby *E. coli* and encourage swarming
- Strength of signal diffuses over space
- Use gaussian distribution to model this

$$J_{cc}(\theta) = \sum_{i=1}^{S} - d^{+} \exp\left(-w^{+}(\theta - \theta_i)^T(\theta - \theta_i)\right) \\ + d^{-} \exp\left(-w^{-}(\theta - \theta_i)^T(\theta - \theta_i)\right)$$

J_{cc} and swarming behaviour