Biomimicry of Foraging for Optimization, Control, and Automation

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Outline

- Philosophy, foraging theory
- Chemotactic behavior (foraging strategy) of *E. coli*
- Bacterial foraging for distributed optimization
- Bacterial foraging for adaptive control
- Automation: Cooperative intelligent control for groups of mobile robots, stable foraging swarms
- Concluding remarks

Philosophy

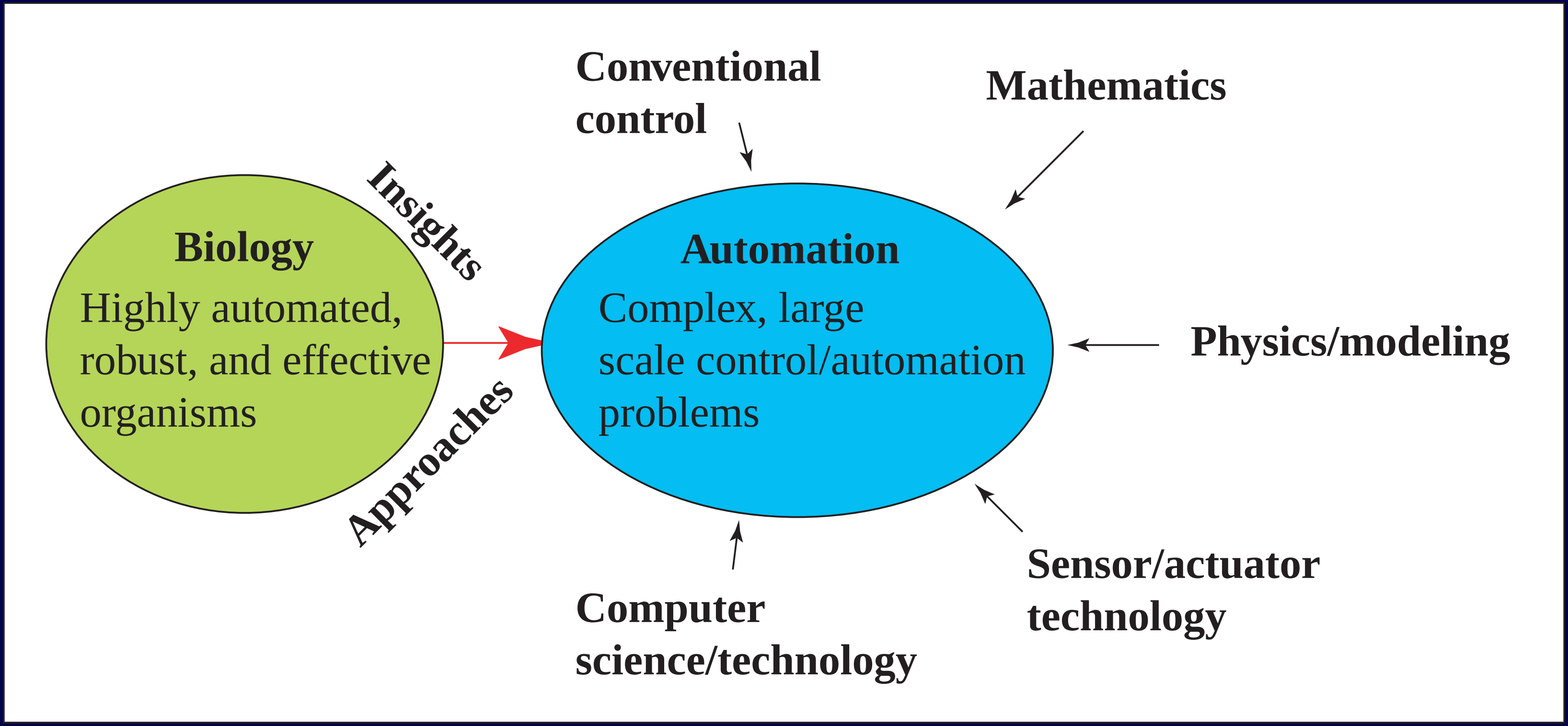

Figure 1: Basic philosophy for this approach.

Foraging Theory

- Animals search for and obtain nutrients to maximize

$$\frac{E}{T}$$

where E is energy obtained per time T

- Foraging constraints: Physiology, predators/prey, environment

→ Evolution optimizes foraging

- Foraging strategy: Find patch, decide whether to enter it and search for food, when to leave patch?

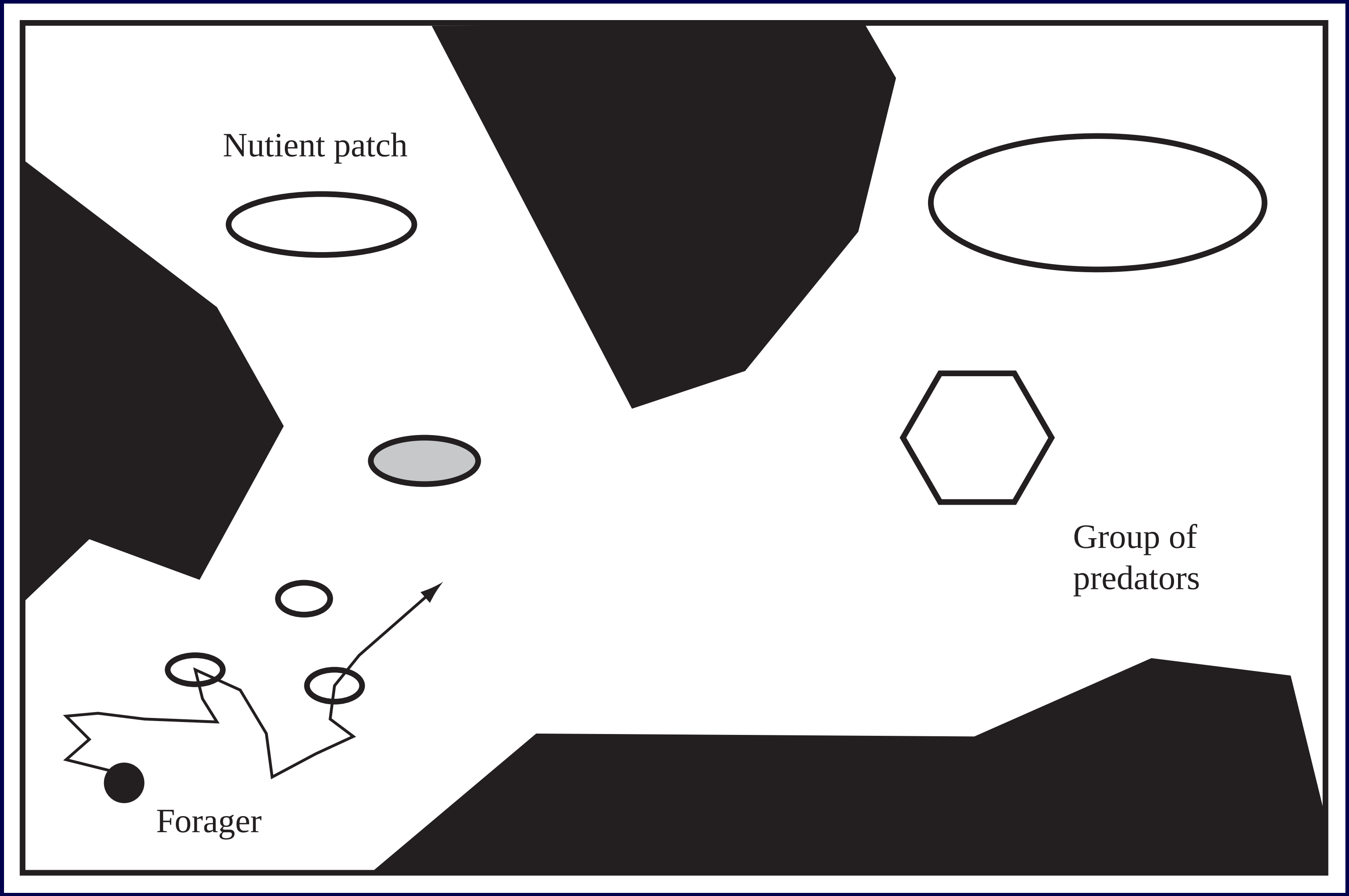

Figure 2: Foraging landscape and scenario.

- Use dynamic programming to find “optimal policies.”
- Search strategies for foraging: cruise (tuna fish), saltatory (birds, fish, insects), and ambush (snakes)

→ Social foraging: Need communications but individuals can gain advantages (more sensors, “gang-up” on large prey, protection, collective intelligence).

- Examples: Bees, ants, fish, birds, wolves, humans

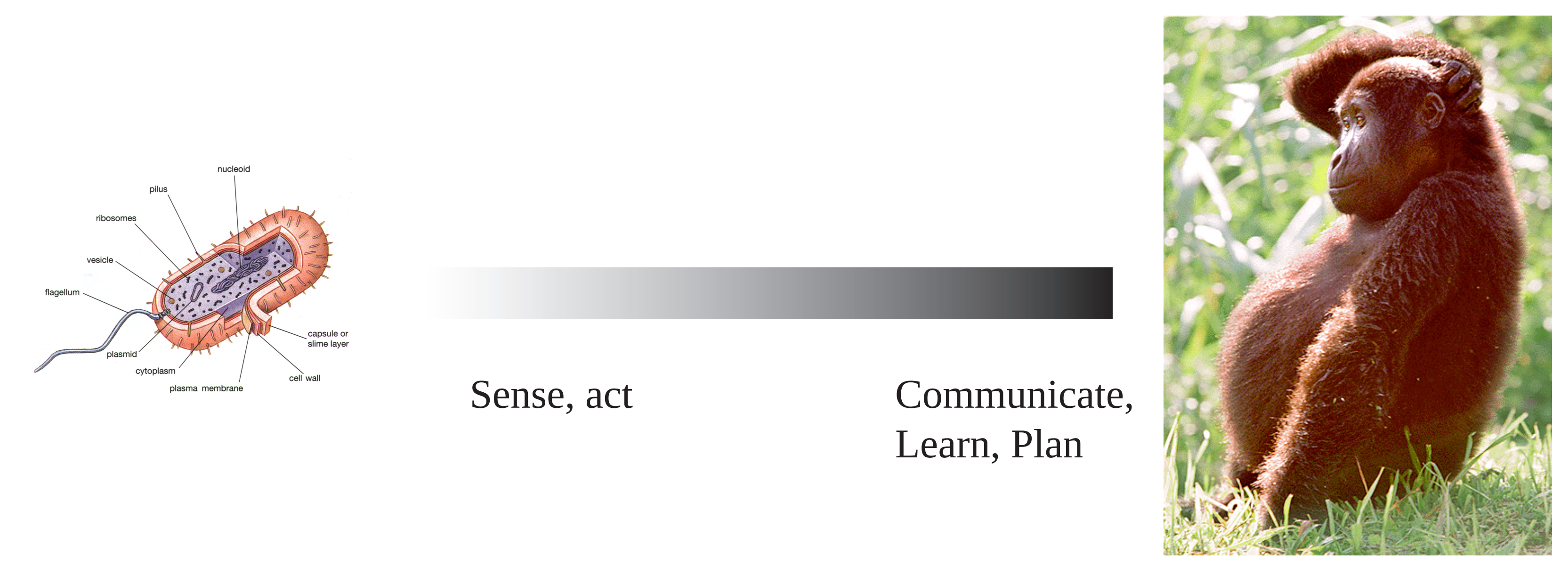

Figure 3: Cognitive spectrum for foraging.

- Entire spectrum interesting from an engineering perspective.
- Let’s start at the bottom...

Chemotactic (Foraging) Behavior of *E. coli*

- *E. coli*: Diameter: $1 \mu m$, Length: $2 \mu m$

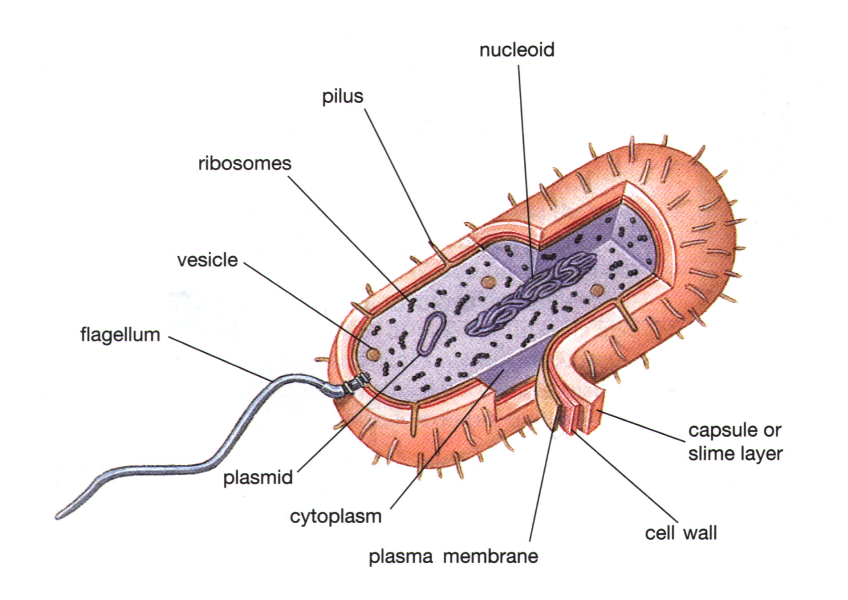

Figure 4: *E. coli* bacterium (from [2]).

- Can reproduce (split) in 20 min.

- *E. coli* in action... (from C. Morton-Firth, Cambridge Univ.)

Motility and Chemotaxis

- Motility via reversible rigid $100 - 200$ rps spinning flagella each driven by a biological “motor”

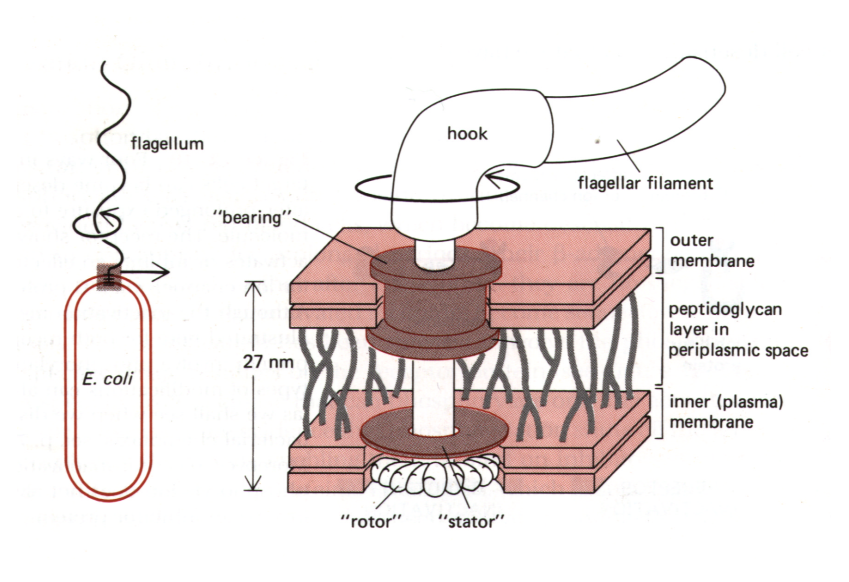

Figure 5: *E. coli* biological “motor” (from [1]).

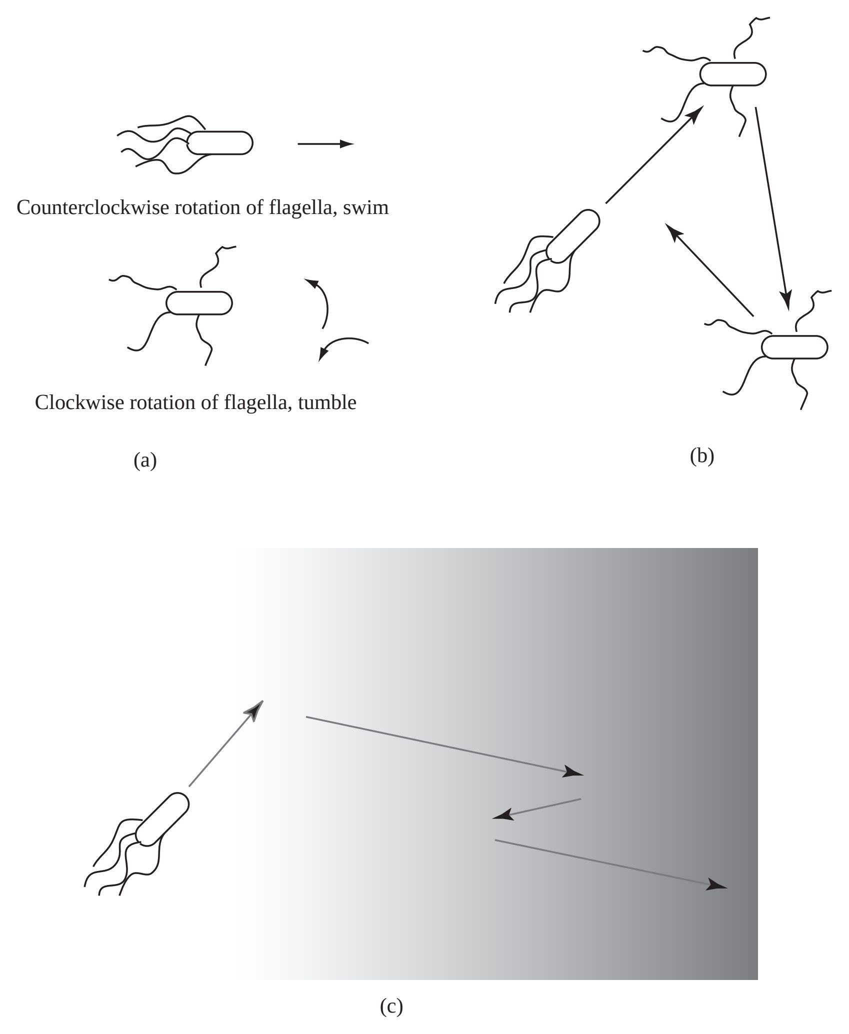

Figure 6: Chemotactic behavior.

Decision Making in Foraging

1. If in neutral medium alternate tumbles and runs

   ⇒ Search

2. If swimming up nutrient gradient (or out of noxious substances) swim longer (climb up nutrient gradient or down noxious gradient)

   ⇒ Seek increasingly favorable environments

3. If swimming down nutrient gradient (or up noxious substance gradient), then search

   ⇒ Avoid unfavorable environments

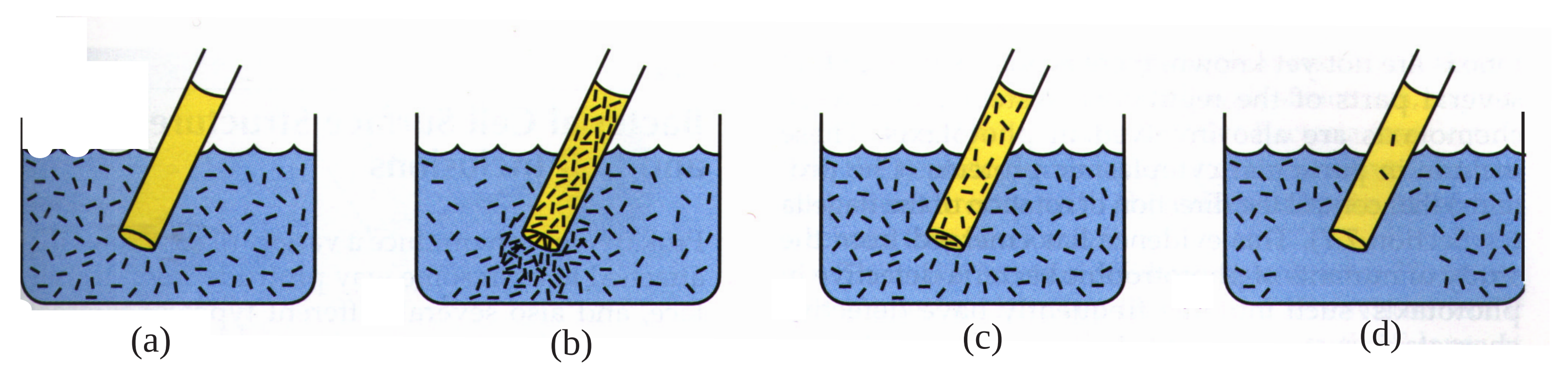

Figure 7: Capillary experiment (from [5]).

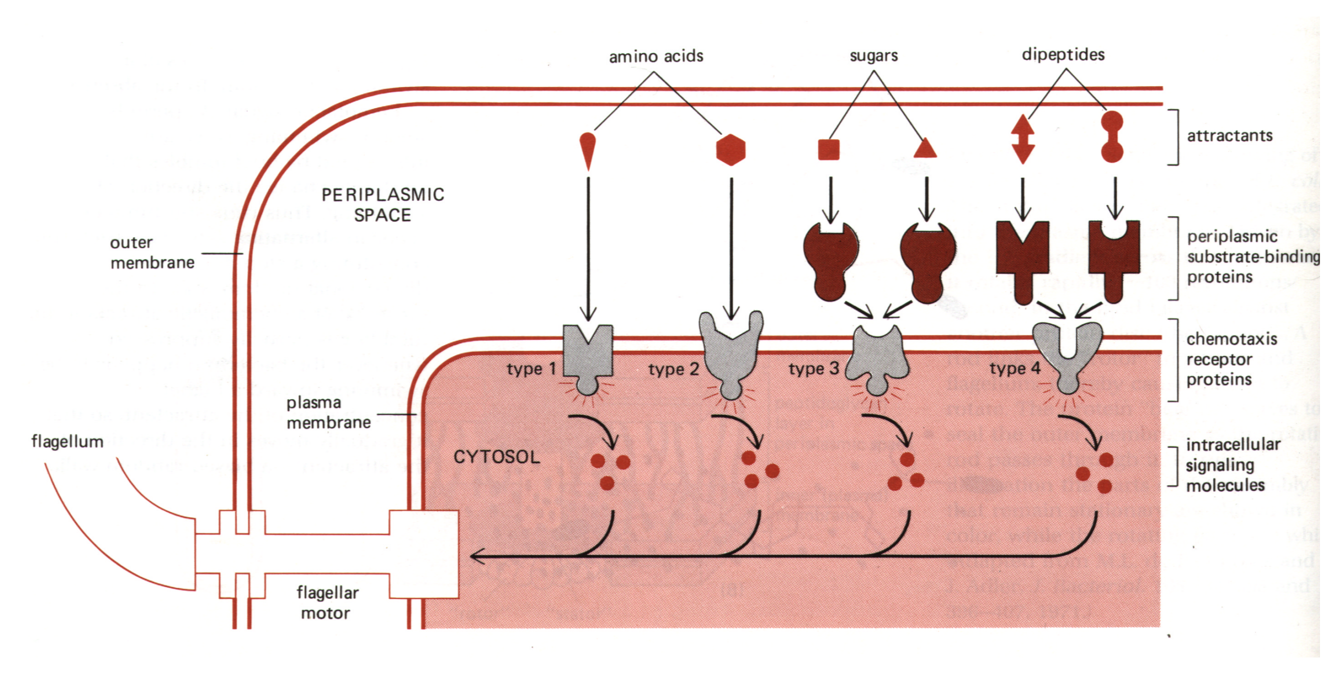

Figure 8: Sensing and control in *E. coli* (from [1]).

- The sensors are very sensitive, and overall there is a "high gain."
- Averages sensed concentrations and computes an approximation to a *time* derivative.

→ Probably the best understood sensory and decision-making system in biology (understood/simulated at molecular level).

Elimination/Dispersal and Evolution

- ➜ Bacteria often killed and dispersed (can be viewed as part of their motility)

- Mutations in *E. coli* affect, e.g., reproductive efficiency at different temperatures, and occur at a rate of about 10^{-7} per gene, per generation.

- *E. coli* occasionally engage in a type of “sex” called “conjugation” (Figure 9)

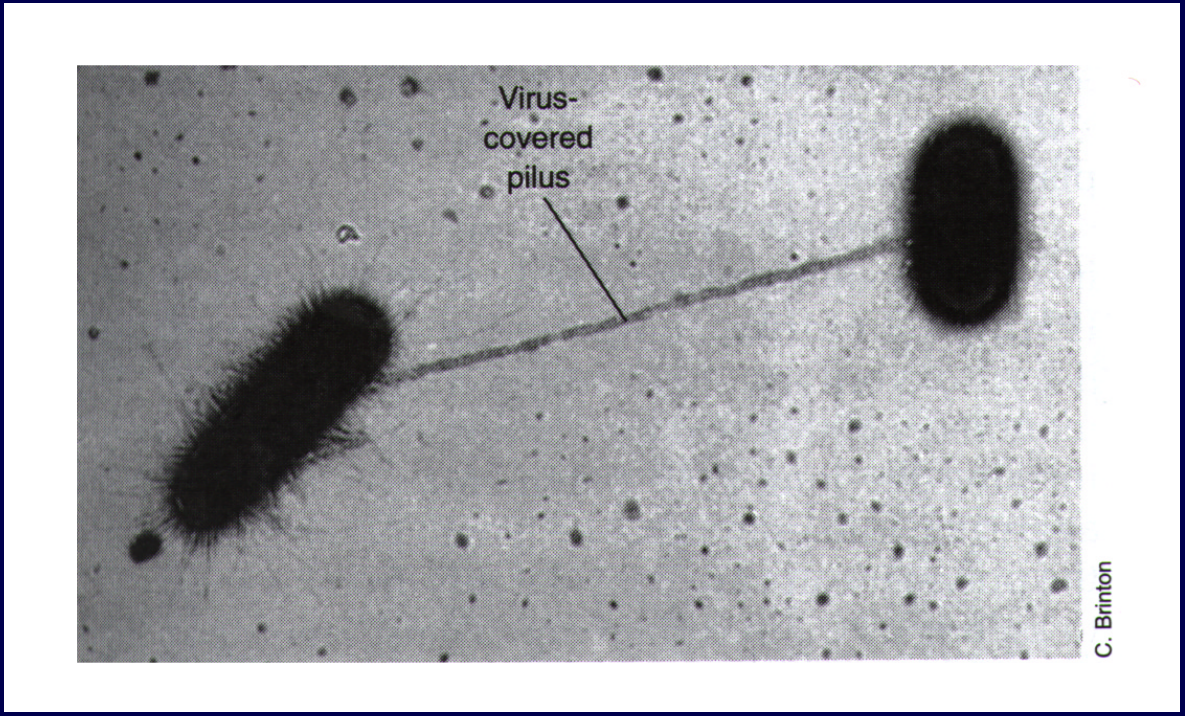

Figure 9: Conjugation in *E. coli* (from [5]).

Other Taxes

1. Change cell shape and number of flagella based on medium!
2. Oxygen (aerotaxis), light (phototaxis), temperature (thermotaxis), magnetic flux lines (magnetotaxis)

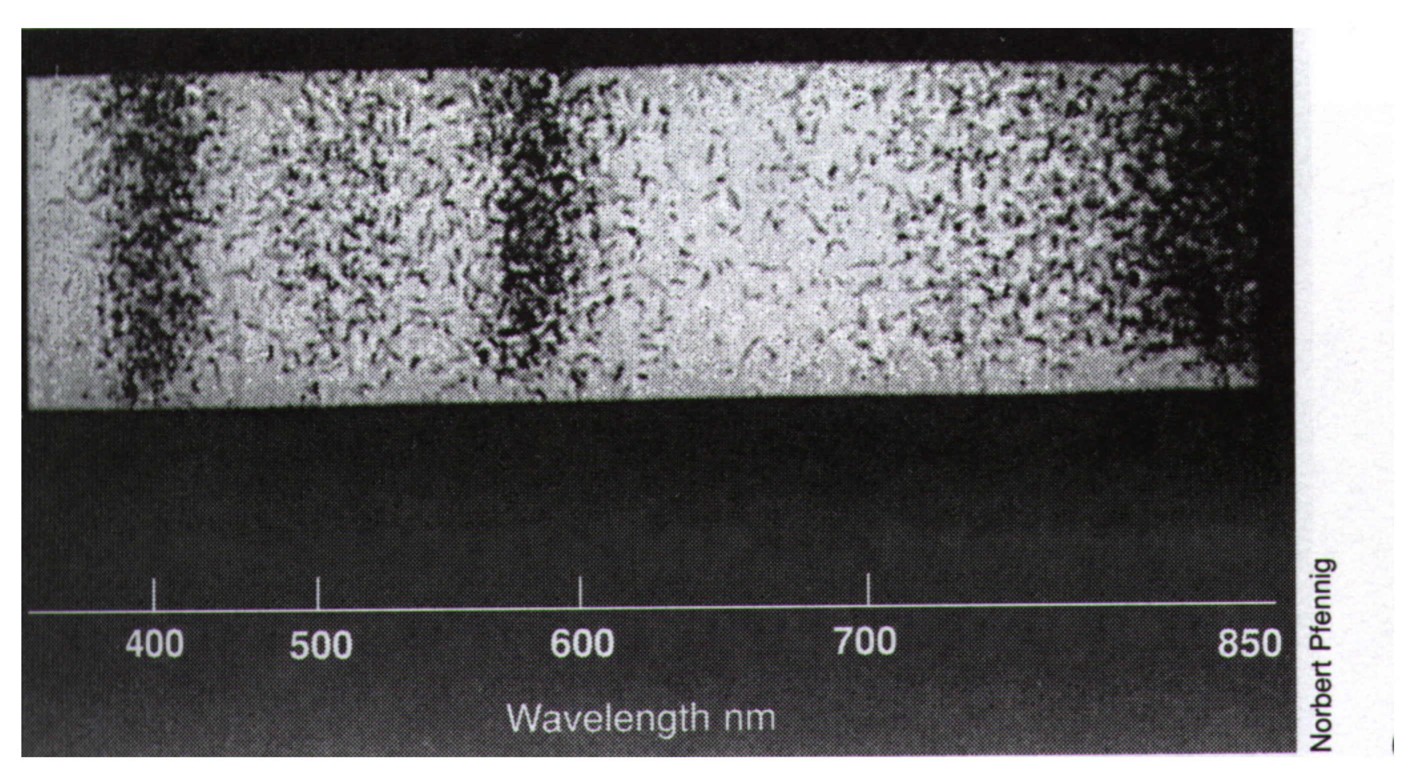

Figure 10: Phototaxis behavior of the phototropic bacterium *Thiospirillum jenense* (from [5]).

Swarms

➔ *E. coli* and *S. typhimurium* can form intricate stable spatio-temporal patterns in certain semi-solid nutrient media

- Radially eat their way through the medium.
- Cell-to-cell attractant signals.
- The bacteria protect each other.

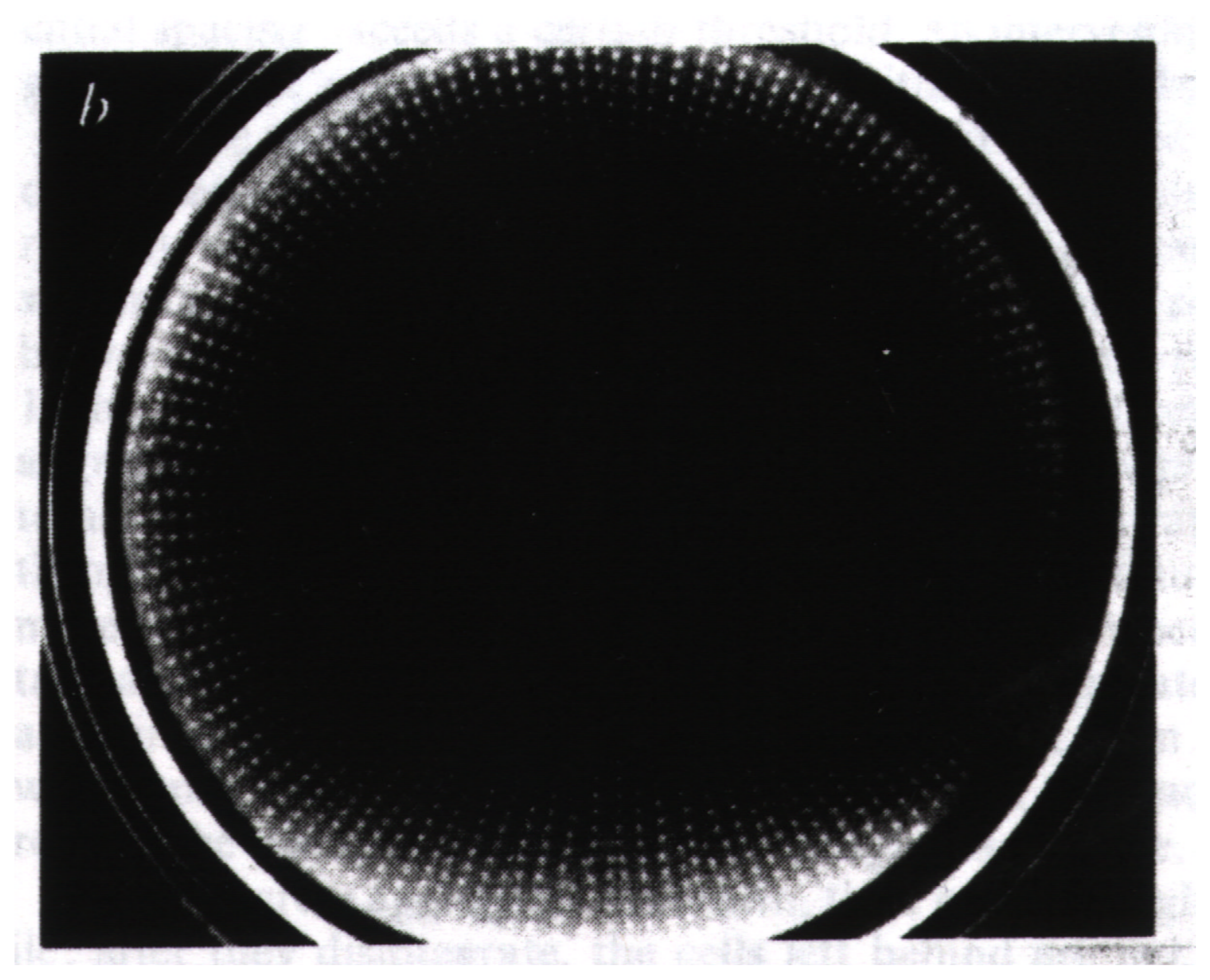

Figure 11: Swarm pattern of *E. coli* (from [3]).

Bacterial Swarm Foraging for Optimization

- Find the minimum of

$$J(\theta), \;\; \theta \in \Re^p$$

when we do not have $\nabla J(\theta)$.

➔ Suppose θ is the position of a bacterium, and $J(\theta)$ represents an attractant-repellant profile so:

1. $J > 0 \Rightarrow$ noxious
2. $J = 0 \Rightarrow$ neutral
3. $J < 0 \Rightarrow$ food

- ➔ Let

$$P(j,k,\ell) = \{\theta^i(j,k,\ell) | i = 1,2,\ldots,S\}$$

be the set of all S bacterial positions at the j^{th} chemotactic step, k^{th} reproduction step, and ℓ^{th} elimination-dispersal event.

- Let $J(i,j,k,\ell)$ denote the cost at the location of the i^{th} bacterium $\theta^i(j,k,\ell) \in \Re^p$.
- Let N_c be the length of the lifetime of the bacteria as measured by the number of chemotactic steps.

- To represent a tumble, a unit length random direction, say $\phi(j)$, is generated; then we let

$$\theta^i(j+1,k,\ell) = \theta^i(j,k,\ell) + C(i)\phi(j)$$

so $C(i) > 0$ is the size of the step taken in the random direction specified by the tumble.

- If at $\theta^i(j+1,k,\ell)$ the cost $J(i,j+1,k,\ell)$ is better (lower) than at $\theta^i(j,k,\ell)$, then another chemotactic step of size $C(i)$ in this same direction will be taken, and repeat that up to a maximum number of steps, N_s.

→ Cell-to-cell signaling via an attractant:

1. Attractants are essentially "food" for other cells (chemotactically attracted to it)
2. Use $J_{cc}^{i}(\theta)$, $i = 1, 2, \ldots, S$, to represent locally secreted food.

- Repel? Via local consumption, and cells are not food for each other. Again, use $J_{cc}^{i}(\theta)$.
- Example: Consider the $S = 2$ case...

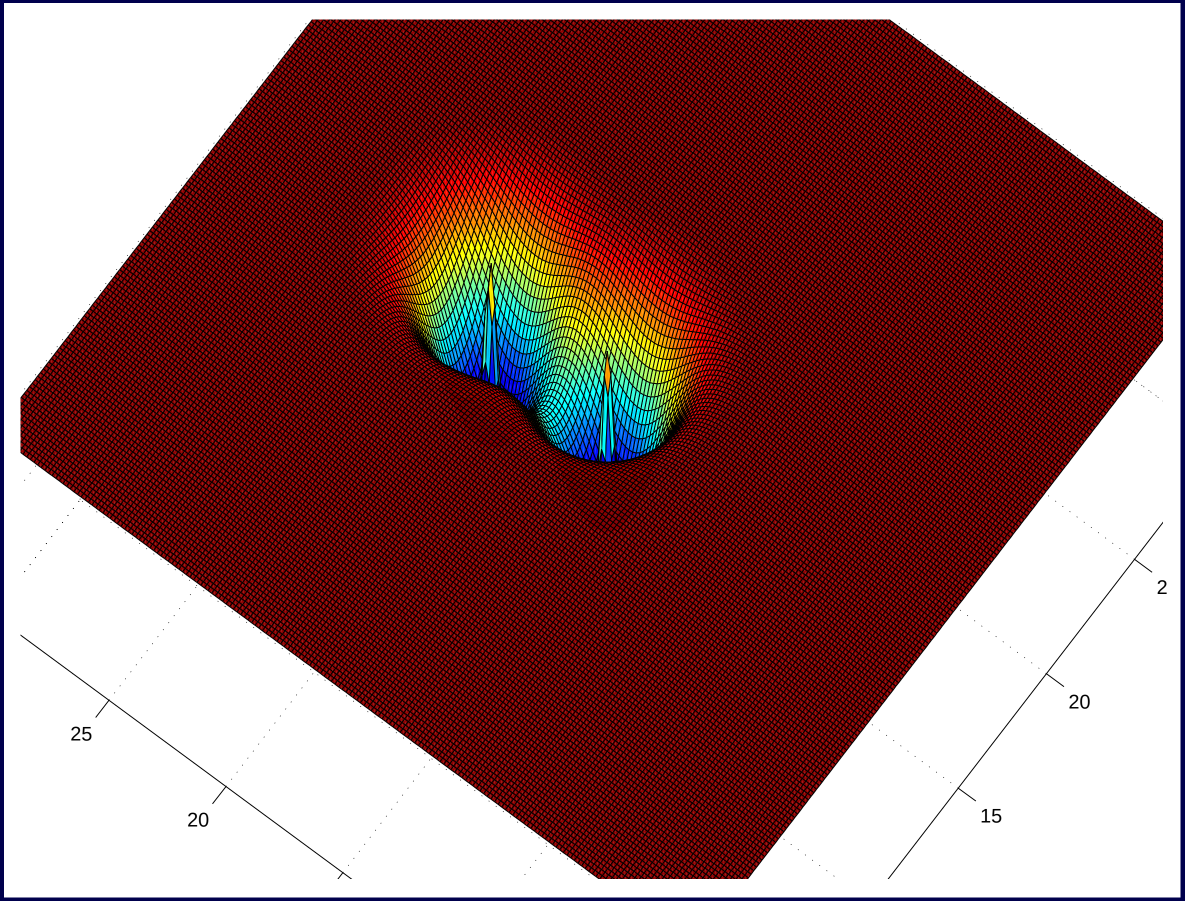

Figure 12: Example cell-to-cell attractant model, $S = 2$.

- For swarming consider minimization of

$$J(i,j,k,\ell) + J_{cc}(\theta)$$

so cells try to find nutrients, avoid noxious substances, and try to move towards other cells, but not too close to them.

- The $J_{cc}(\theta)$ function dynamically deforms the search landscape to represent the desire to swarm.

- Take N_{re} reproduction steps.

- For reproduction, healthiest bacteria (ones that have lowest accumulated cost over their lifetime) split, and then kill other unhealthy half of population.
- Let N_{ed} be the number of elimination-dispersal events (for each one, each bacterium is subjected to elimination-dispersal with probability p_{ed}).
- Biologically valid model? Capturing gross characteristics of chemotactic hill-climbing and swarming.

Example: Function Optimization

- Find minimum of function in Figure 13 ($[15, 5]^\top$ is the global minimum point, $[20, 15]^\top$ is a local minimum).
- Standard ideas from optimization theory can be used to set the algorithm parameters.

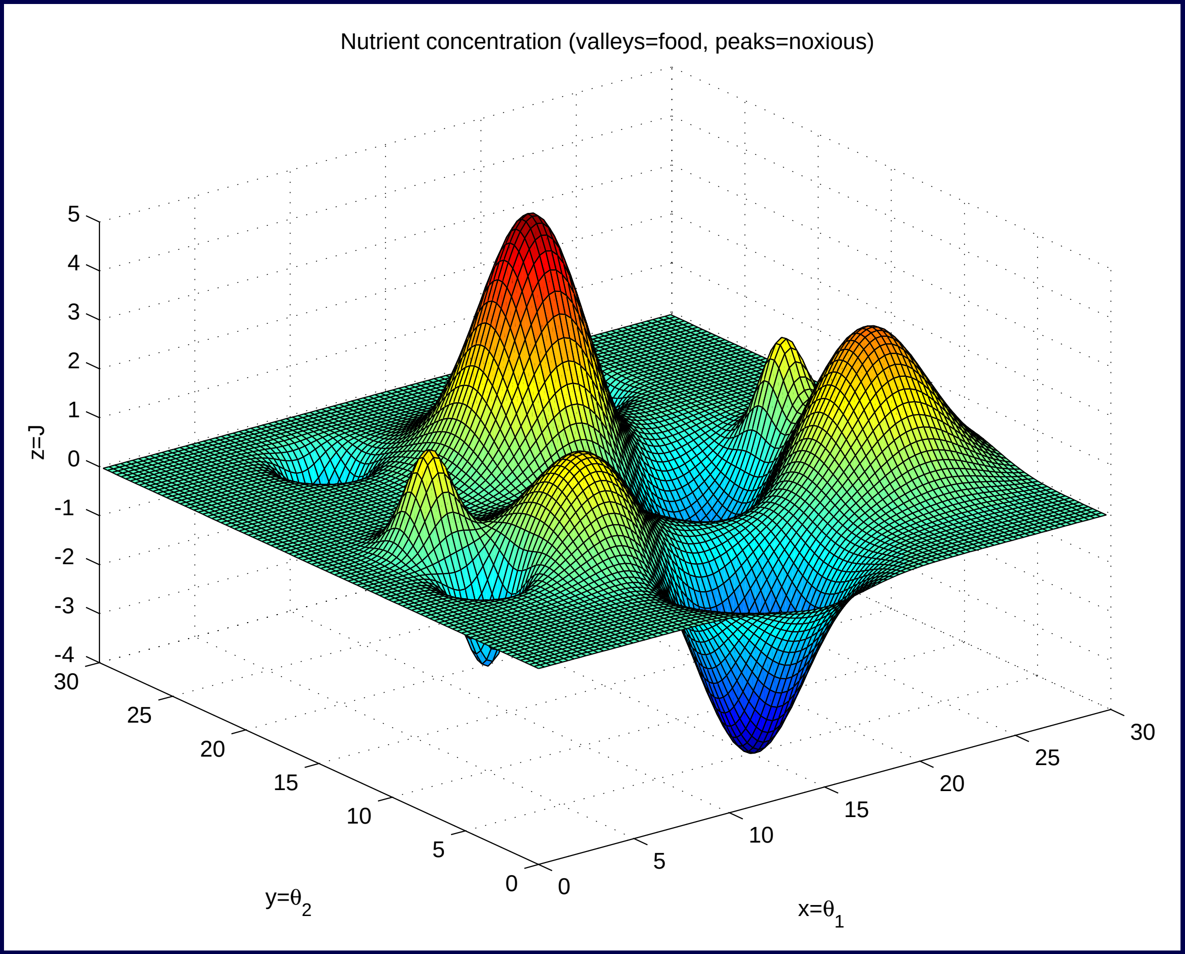

Figure 13: Function with multiple extremum points.

➜ No swarming:

- $S = 50$, $N_c = 100$, $C(i) = 0.1, i = 1, 2, \ldots, S$, $N_s = 4$ (a biologically-motivated choice)
- $N_{re} = 4$, $N_{ed} = 2$, $p_{ed} = 0.25$,
- Random initial bacteria distribution.

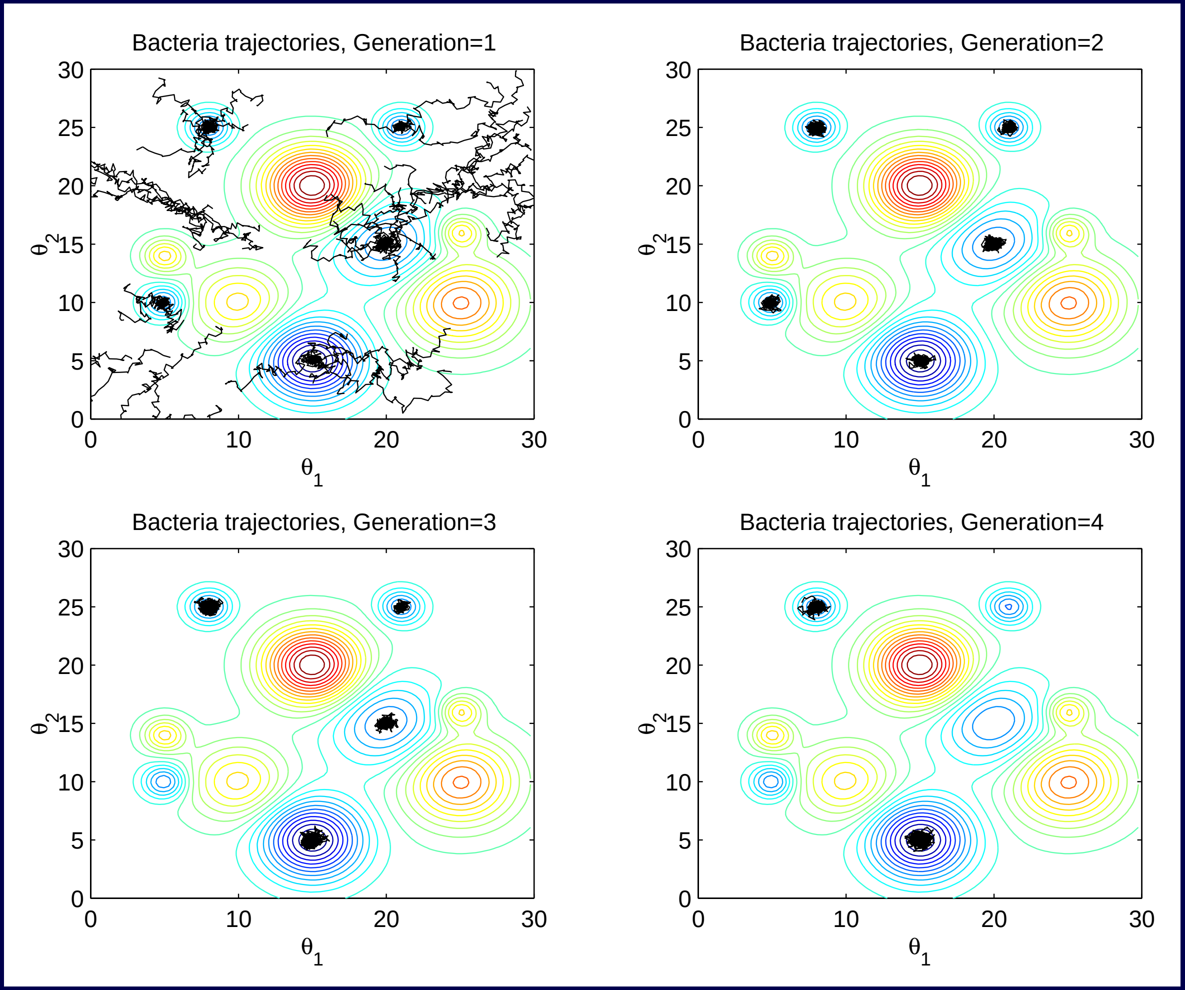

Figure 14: Bacterial motion trajectories, generations 1-4.

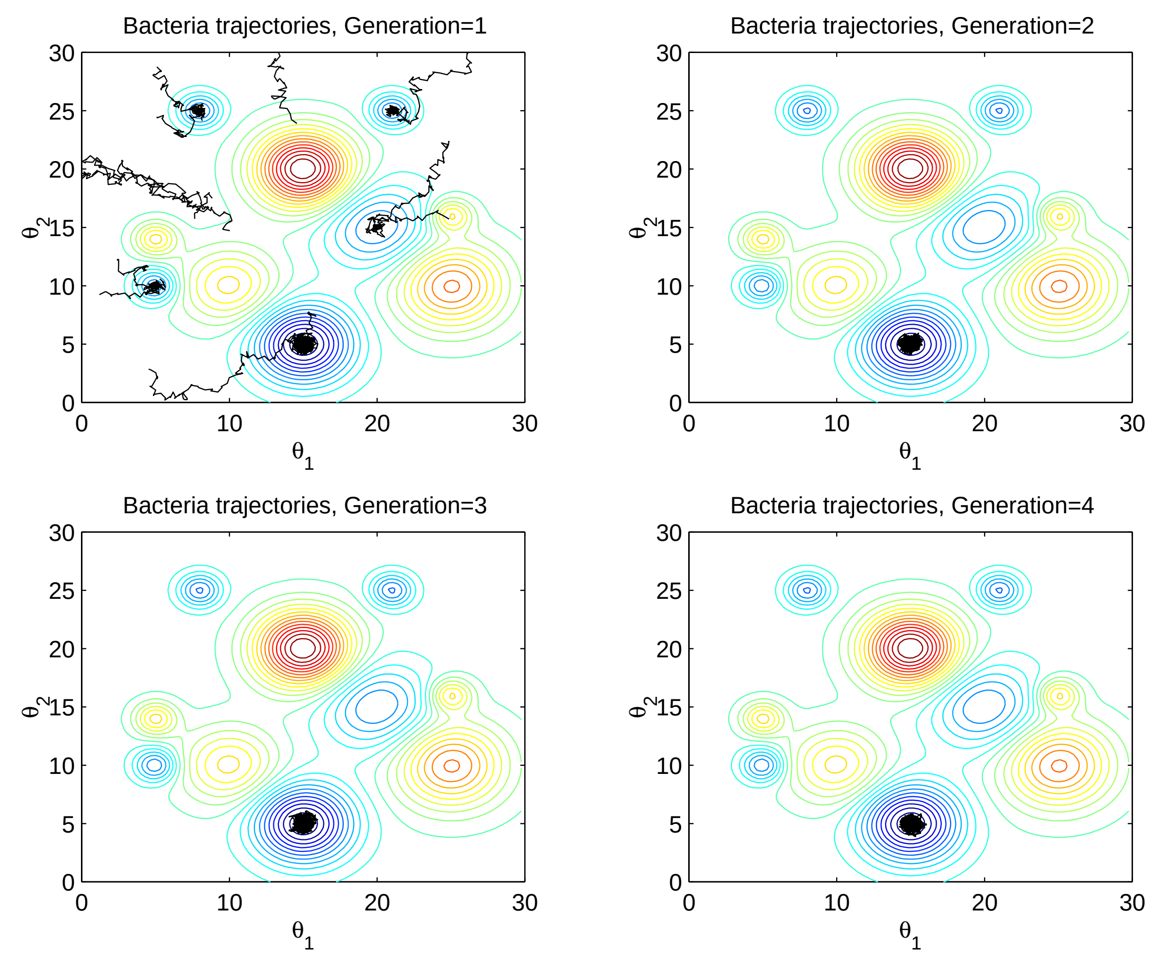

Figure 15: Bacterial motion trajectories, generations 1-4, after an elimination-dispersal event.

→ Swarm effects:

- Emulate Figure 11 by considering optimization over Figure 16.
- Initially, place all cells at the peak $[15, 15]^\top$.

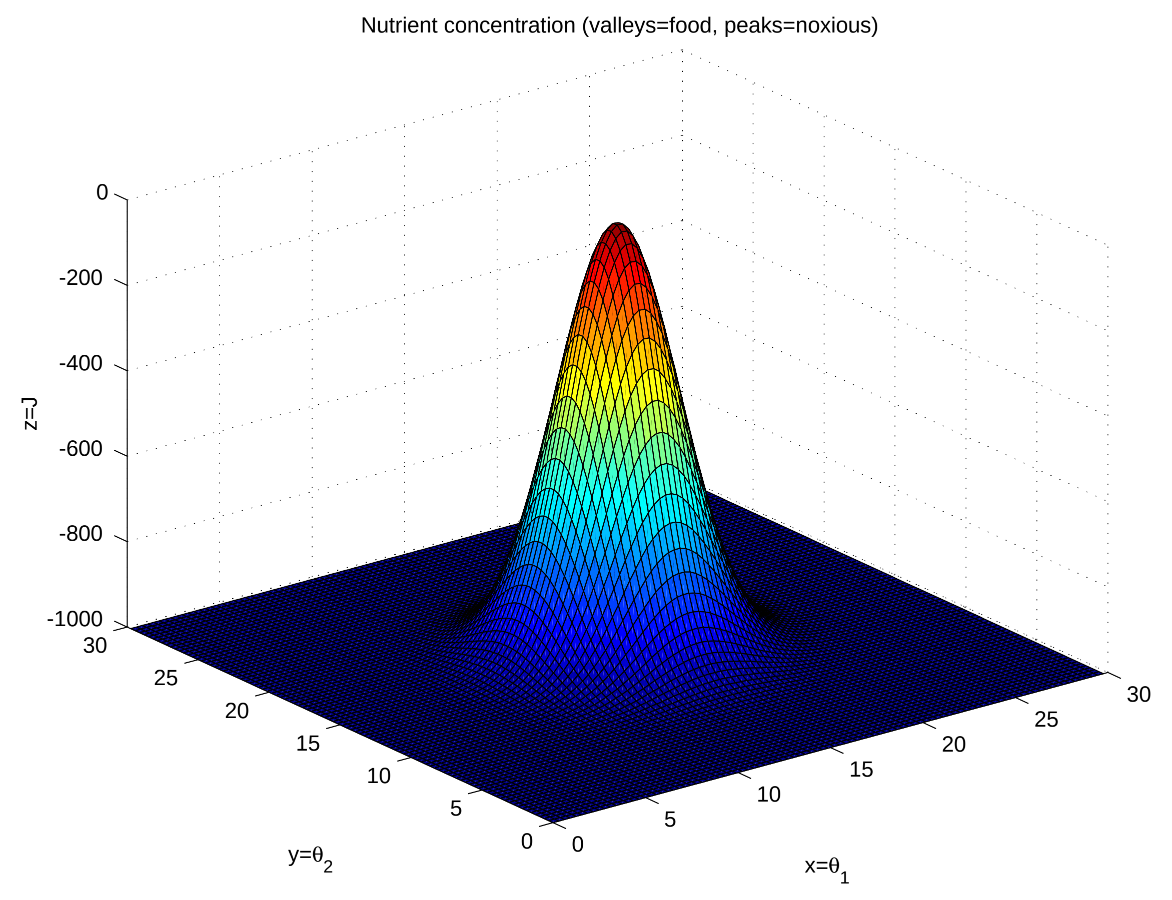

Figure 16: A nutrient surface for testing swarming.

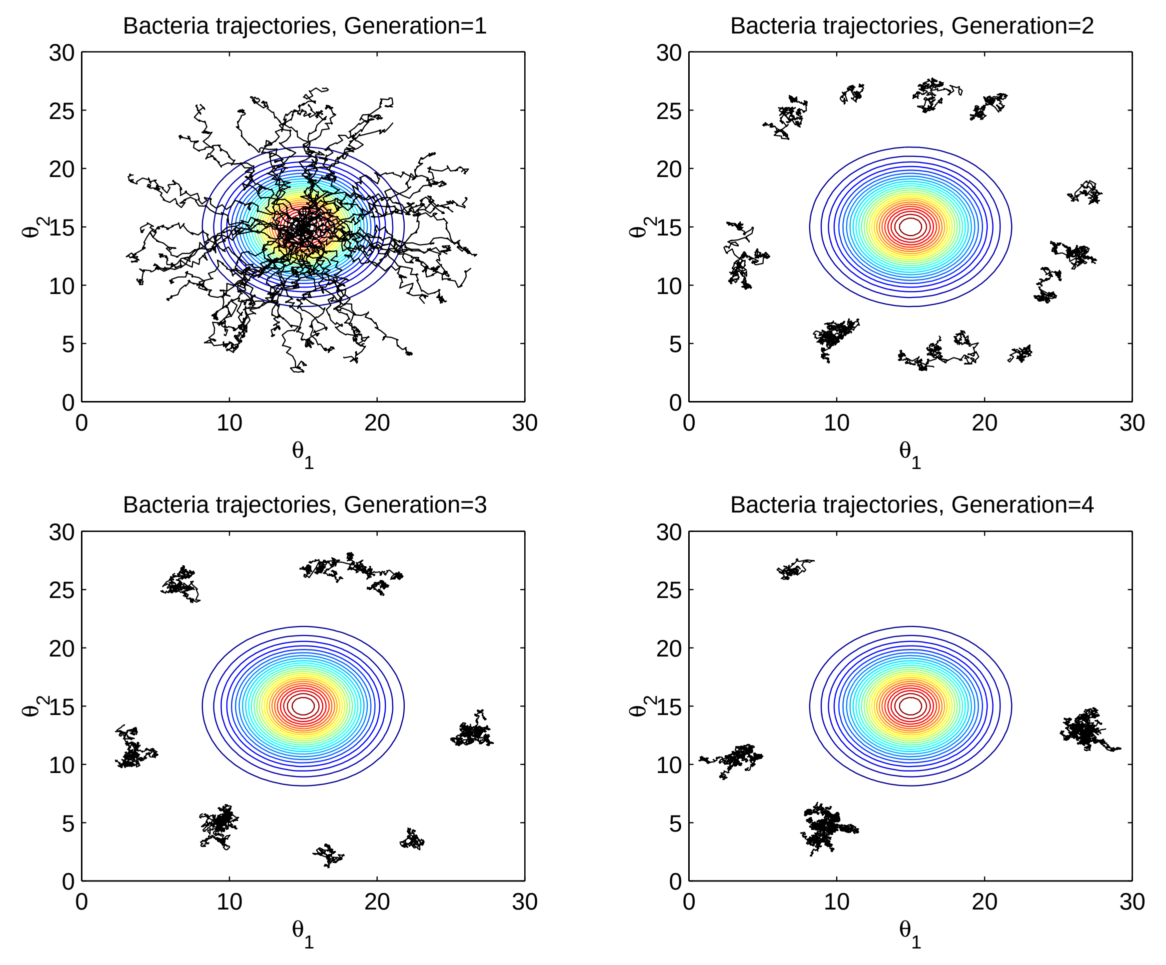

Figure 17: Swarm behavior of *E. coli* on a test function.

Take a Step Up the Cognitive Spectrum for Foraging

★ *Archangium violaceum* foraging for *Sarcina* (*Myxobacteria* web page, M. Dworkin, Univ. Minnesota).

- *M. xanthus*: Social and adventurous swarming (web page of Dale Kaiser, Stanford Univ.)

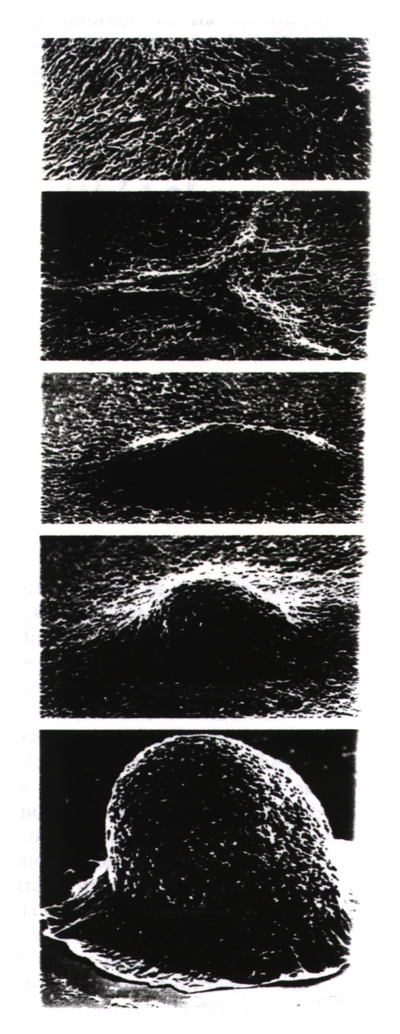

Figure 18: *M. xanthus* mound formation (from [4]).

- Cellular automata-based optimization
- Resulting swarm dynamics “emerge”:

1. Formation (aggregation) events
2. Size
3. Location
4. Motility (move faster as individuals than in groups)

→ Balance between desire to individually forage and to form swarm aggregates is delicate.

Discussion

- Optimization methods: Related to stochastic approximation, genetic algorithms. Comparative analysis important! (J. Spall)

→ Evolution made foraging search strategies "optimal" for the environment of the bacteria (class of cost functions)—perhaps not our engineering problems!

★ What is the value? To be determined, but for now: Science, metaphor for control and automation?

Bacterial Foraging for Adaptive Control

- On-line function approximation view: learn a nonlinear plant mapping (indirect) or controller mapping (direct)

→ View learning as foraging for good information

- Social foraging $\Rightarrow$ foragers share information and give hints to each other about how to find good information

→ Foraging $=$ on-line optimization $\Rightarrow$ can use it for on-line parameter adjustments in adaptive control

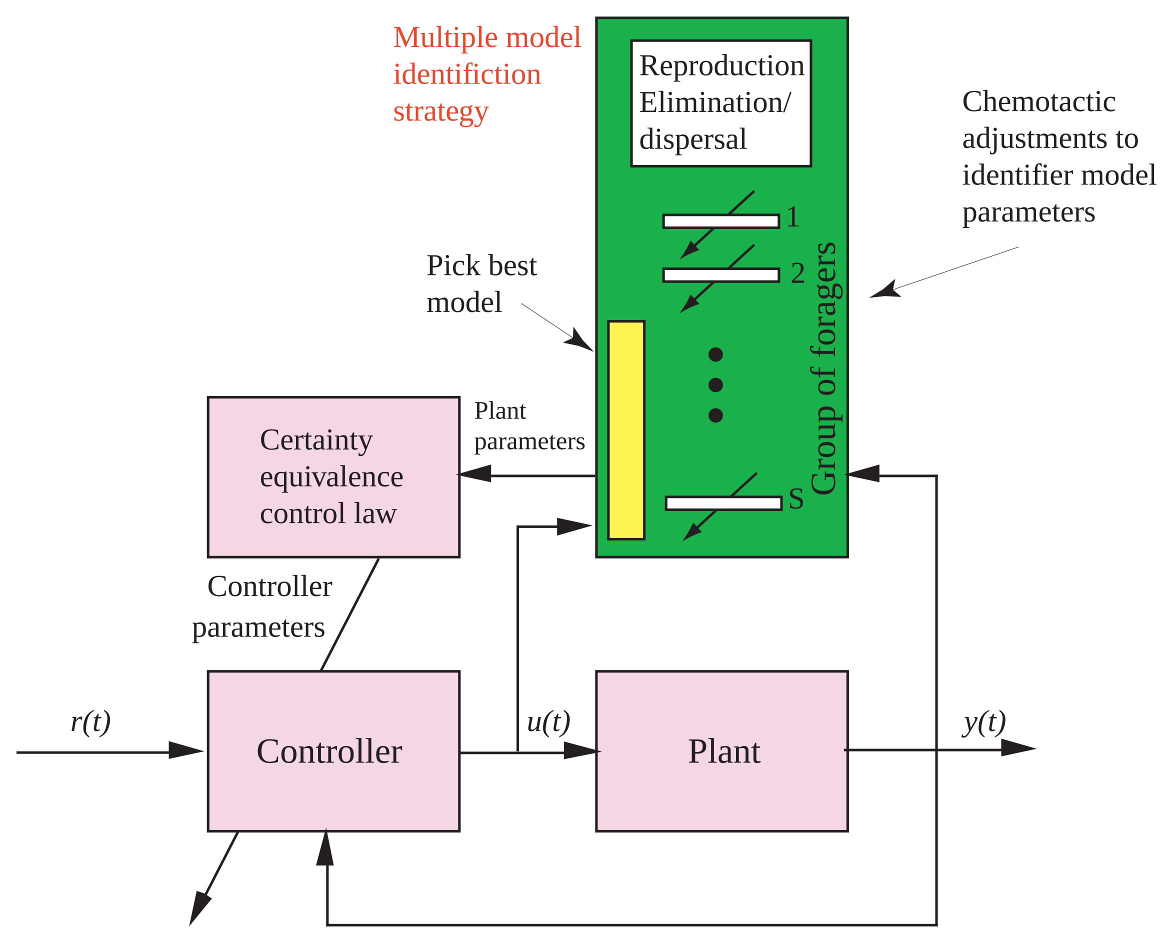

Figure 19: Swarm foraging in adaptive control.

→ Adaptive model predictive control is also possible.

- Process control application: Simple "surge tank" liquid level control (just to illustrate the idea)

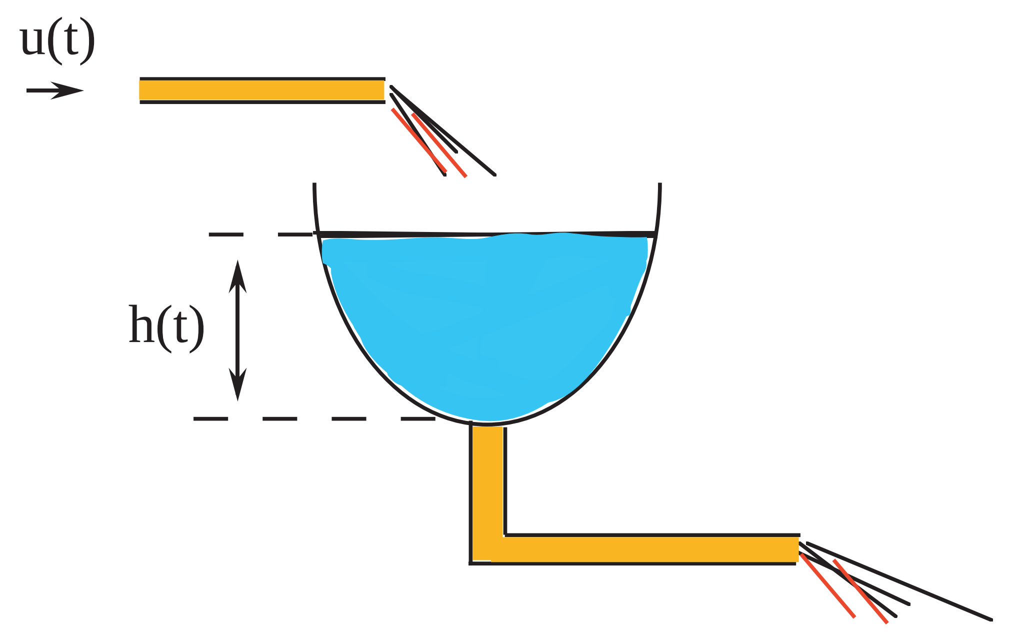

Figure 20: Surge tank.

- Discretize:

$$\frac{dh(t)}{dt} = \frac{-\bar{d}\sqrt{2gh(t)}}{A(h(t))} + \frac{\bar{c}}{A(h(t))}u(t)$$

- $u(t)$, input (saturated); $h(t)$ is liquid level (saturated), $r(t)$ be the desired level, $e(t) = r(t) - h(t)$
- $A(h(t)) = |\bar{a}h(t) + \bar{b}|$ is the (unknown) tank cross-sectional area

★ **Approach:** Tune a set of (affine) approximators to match plant nonlinearities ($p = 2$).

- **Forager's position:** $\theta^i = [\theta^i_\alpha, \theta^i_\beta]^\top$, $i = 1, 2, \ldots, S$ ($S = 10$)

- **Cost:** Sum of squares of $N = 100$ past values for each model.

- **Parameter adjustment:** *E. coli* chemotactic (interleaved with time steps), but no forager-forager communications.

★ Tracking performance:

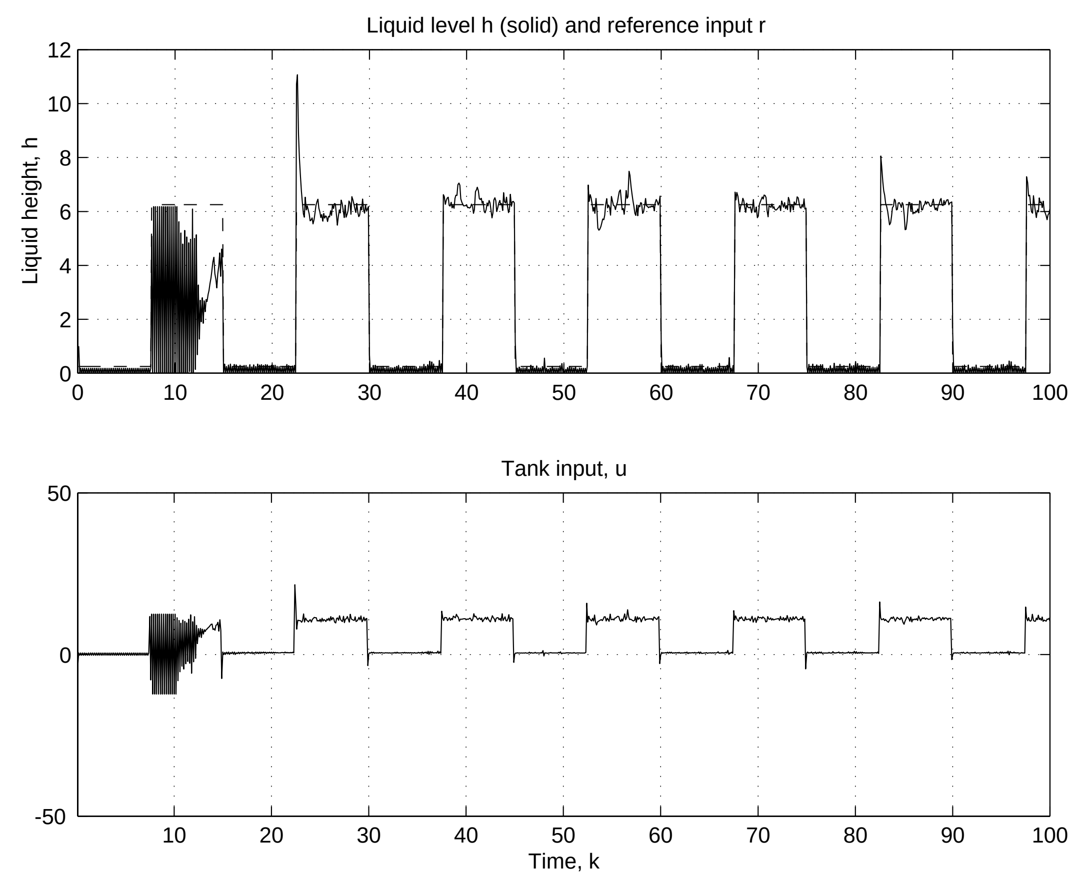

Figure 21: Closed-loop response.

★ Estimator performance:

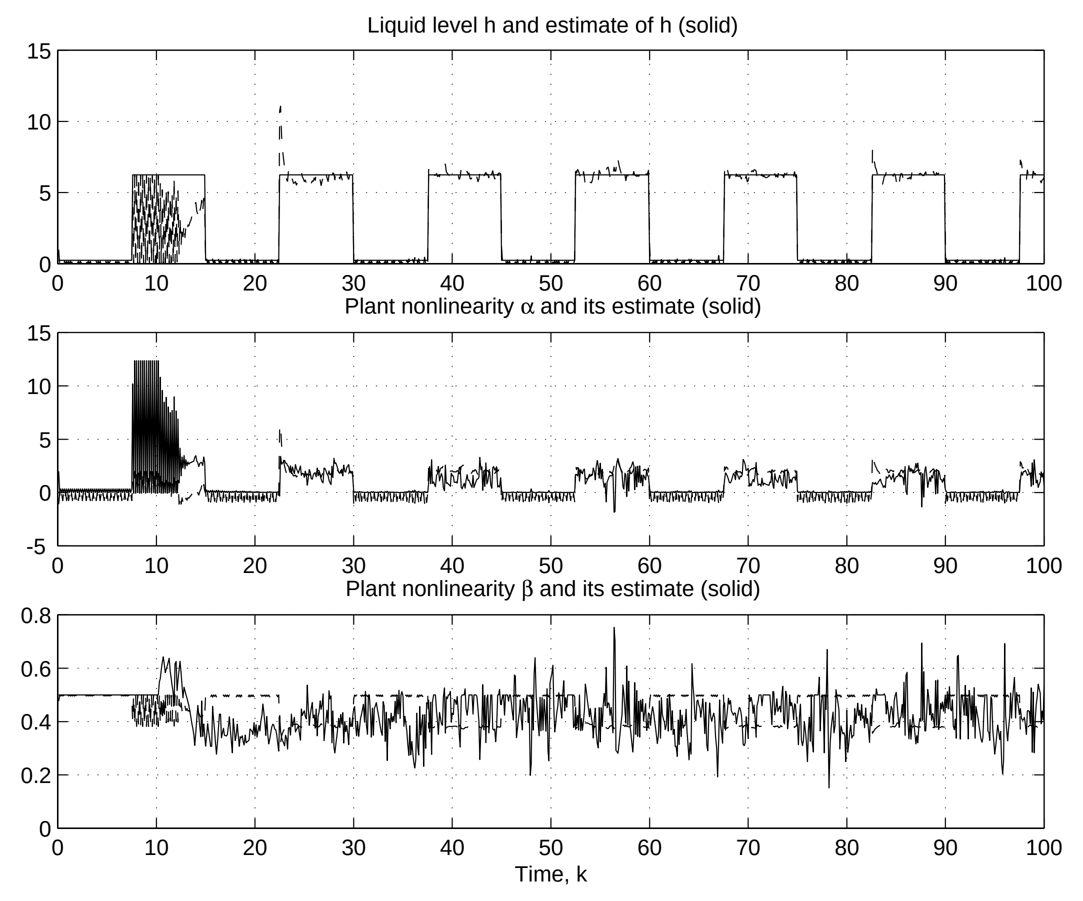

Figure 22: Estimates of liquid level and nonlinearities.

★ Best forager:

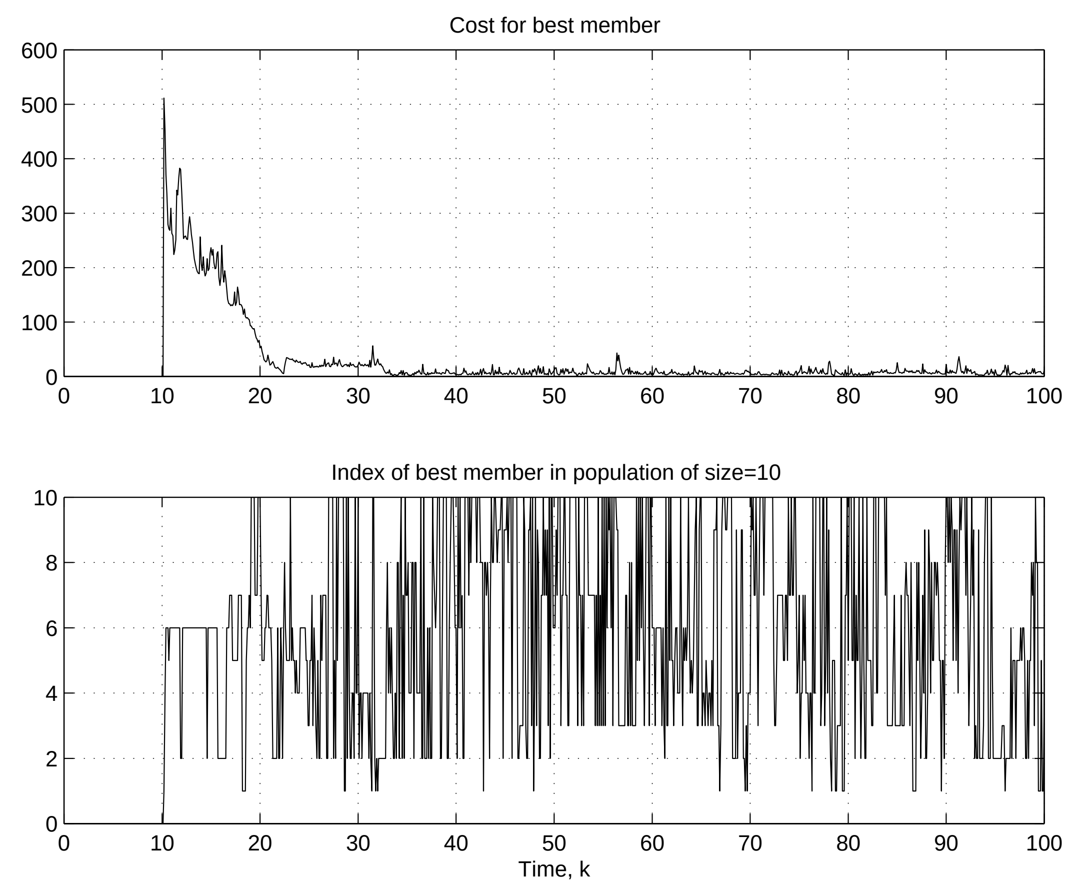

Figure 23: Best cost, index of best forager.

Autonomous Robots: Pollution Clean-Up

(M. Polycarpou)

- ➔ Robots for search/removal of dispersed pollutant.
- ➔ Use many simple inexpensive robots (why?).
  - Communication constraints: Locality, bandwidth, and delays
  - On-board functionality: Computer, signal processing, control, fuel. How much?
  - Risks: Avoid certain locations.

- ★ *E. coli* “vehicles”—a nanotechnologist’s dream!

- Use an *E. coli* (*M. xanthus*) search strategy?
- Bacterial sensing, locomotion, and decision-making strategies are limited.
- Their foraging is optimized for a certain environment, probably not this one!

★ Foraging principle: Optimization/search is a central concept.

★ Evolutionary principle: Vehicle and environment dictate cooperative strategy.

Intelligent Group Foraging (M. Baum)

- What if our forager has capabilities for planning, attention, learning, and sophisticated communications?
- Learning/planning approach: construct cognitive maps, predict using these, and share the maps
  - Relevant optimization theory: Real-time “surrogate model methods.”
  - Suppose we think of the density of a pollutant in a region as an unknown map.

Distributed Map Learning

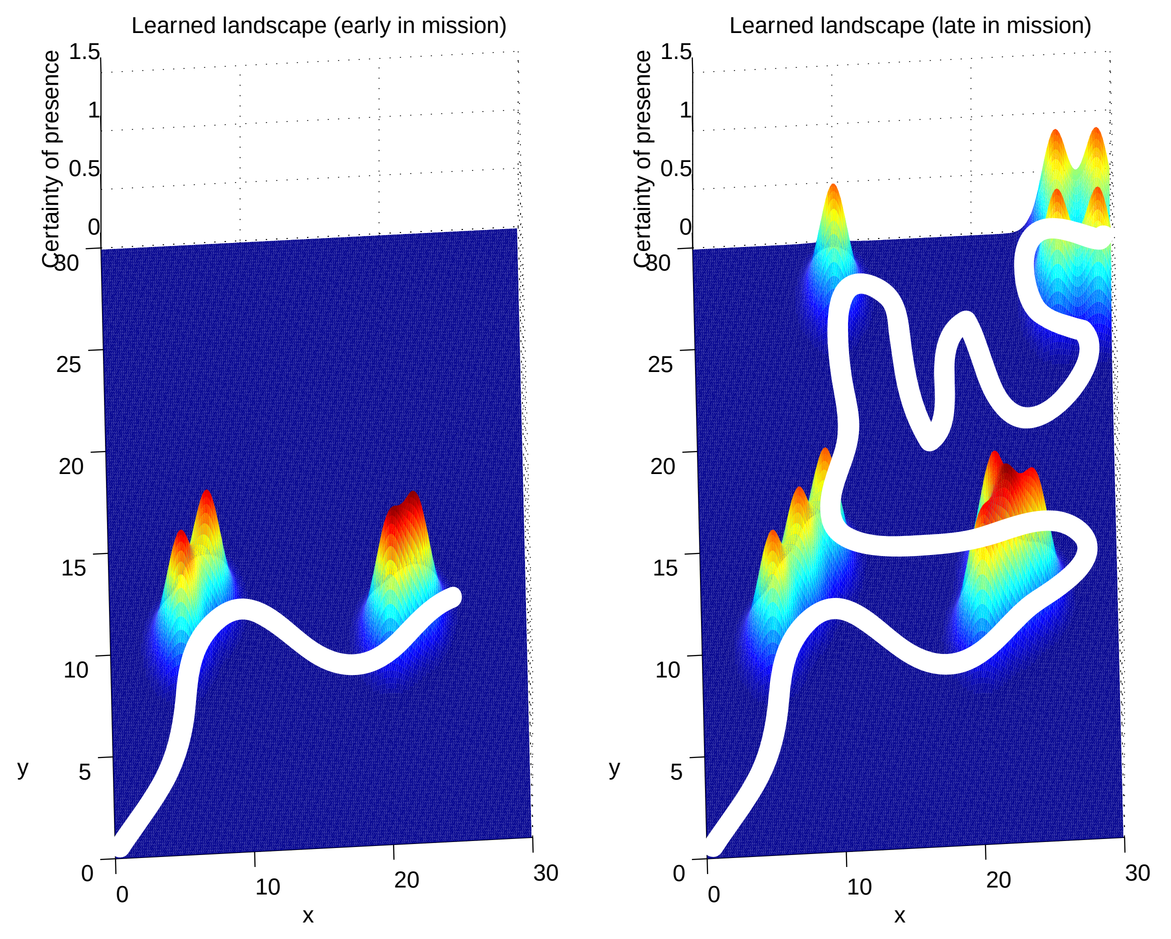

Figure 24: Robot learning a landscape.

- Other maps: Importance of various pollutants, where can get stuck
- Distributed Learning and Coordination: How to coordinate learning via sharing of maps? When to seek more information (risky) vs. when to focus on gathering more information in a previously visited area?
- Distributed Planning: On shared maps.

→ Research Challenges: Guaranteed performance, stability, convergence, robustness

Stable Foraging Vehicular Swarms (Y. Liu)

- Need underlying mechanisms for group cohesion (stability) for goal-directed behavior that cope with vehicular/communication constraints.

★ Cohesive swarm behavior:

Concluding Remarks

- ✓ Foraging = optimization/search ⇒ methods for control/automation.
- ✓ Adaptive control (but need stability/convergence analysis).
- ✓ Biomimicry of intelligent foraging for distributed cooperative control of groups of mobile robots.
- ✓ Engineering applications... and many research directions.

References

[1] B. Alberts, D. Bray, J. Lewis, M. Raff, K. Roberts, and J.D. Watson. *Molecular Biology of the Cell*. Garland Publishing, NY, 2nd edition, 1989.

[2] T. Audesirk and G. Audesirk. *Biology: Life on Earth*. Prentice Hall, NJ, 5 edition, 1999.

[3] E.O. Budrene and H.C. Berg. Dynamics of formation of symmetrical patterns by chemotactic bacteria. *Nature*, 376:49–53, 1995.

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➔ Paper submitted to IEEE Control Systems Magazine.

➔ Also, in book to appear: “Intelligent Control: Biomimicry for Optimization, Adaptation, and Decision-Making in Computer Control and Automation”