VI
Autonomous Agents
&
Self-Organization

Autonomous Agent

- “a unit that interacts with its environment (which probably consists of other agents)
- but acts independently from all other agents in that it does not take commands from some seen or unseen leader,
- nor does an agent have some idea of a global plan that it should be following.”

—Flake (p. 261)

A. Schools, Flocks, & Herds

"and the thousands of fishes moved
as a huge beast, piercing the water.
They appeared united, inexorably
bound to a common fate.
How comes this unity?"

— anon., 17th cent.

images from EVALife site

Coordinated Collective Movement

- Groups of animals can behave almost like a single organism
- Can execute swift maneuvers
  - for predation or to avoid predation
- Individuals rarely collide, even in frenzy of attack or escape
- Shape is characteristic of species, but flexible

Adaptive Significance

- Prey avoiding predation
- More efficient predation by predators
- Other efficiencies

Avoiding Predation

- More compact aggregation
  - predator risks injury by attacking
- Confusing predator by:
  - united erratic maneuvers (e.g. zigzagging)
  - separation into subgroups (e.g., flash expansion & fountain effect)

Flash Expansion

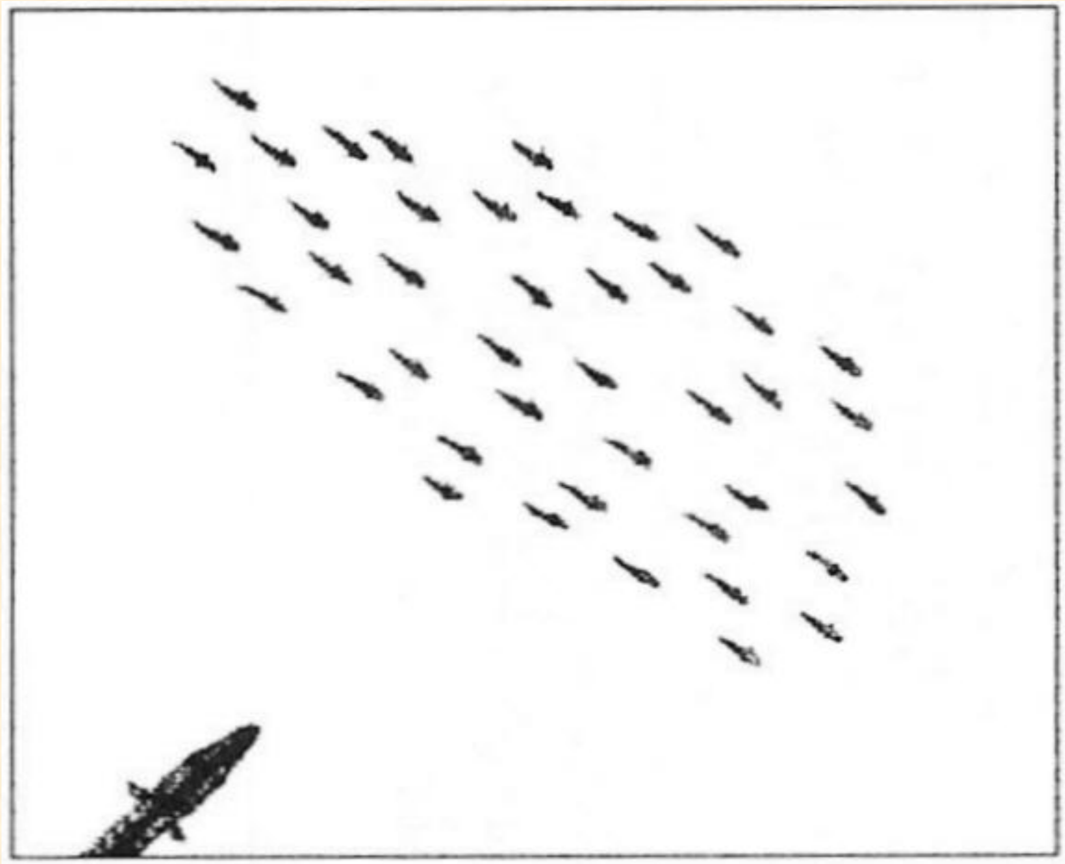


Fig. from Camazine & al., *Self-Org. Biol. Sys.*

Flash Expansion

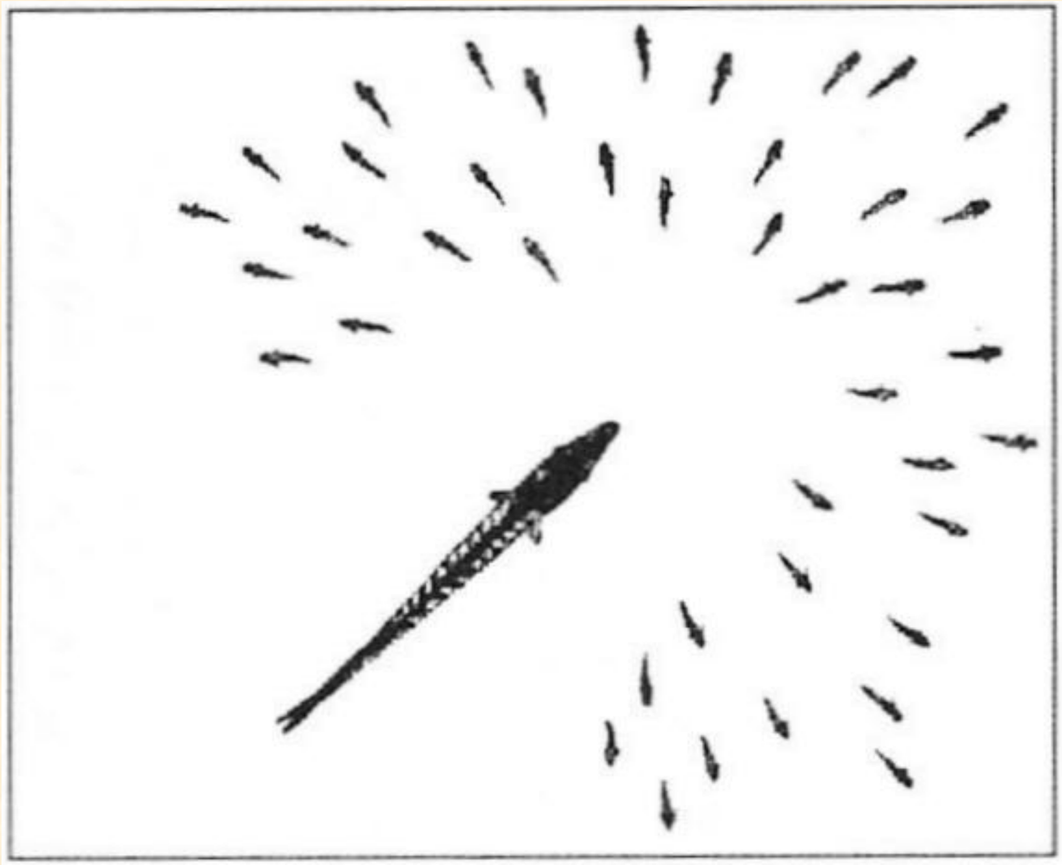


Fig. from Camazine & al., *Self-Org. Biol. Sys.*

Fountain Effect

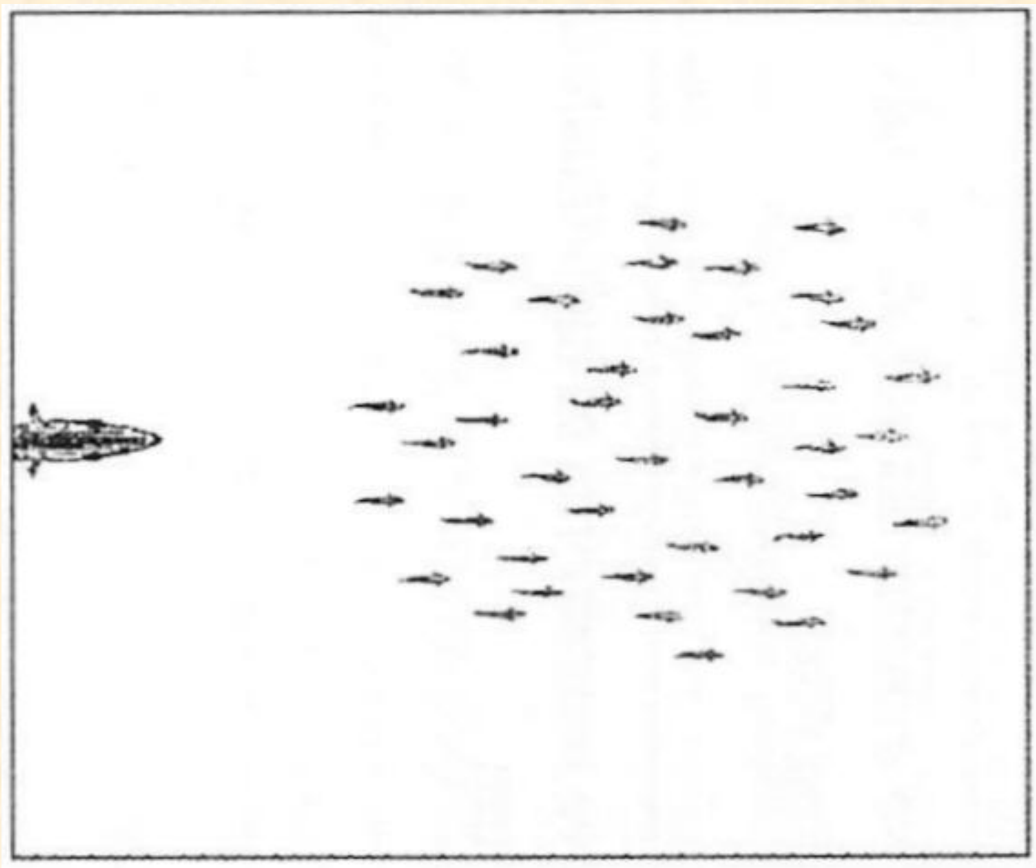


Fig. from Camazine & al., *Self-Org. Biol. Sys.*

Fountain Effect

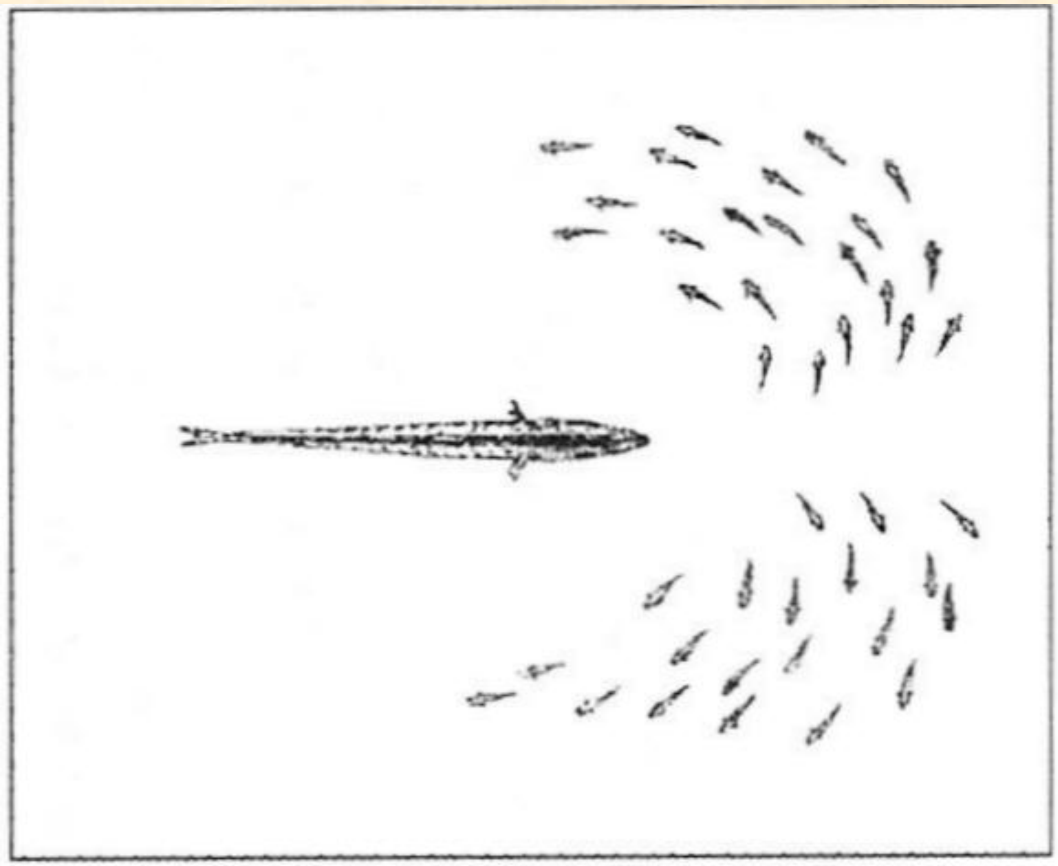


Fig. from Camazine & al., *Self-Org. Biol. Sys.*

Fountain Effect

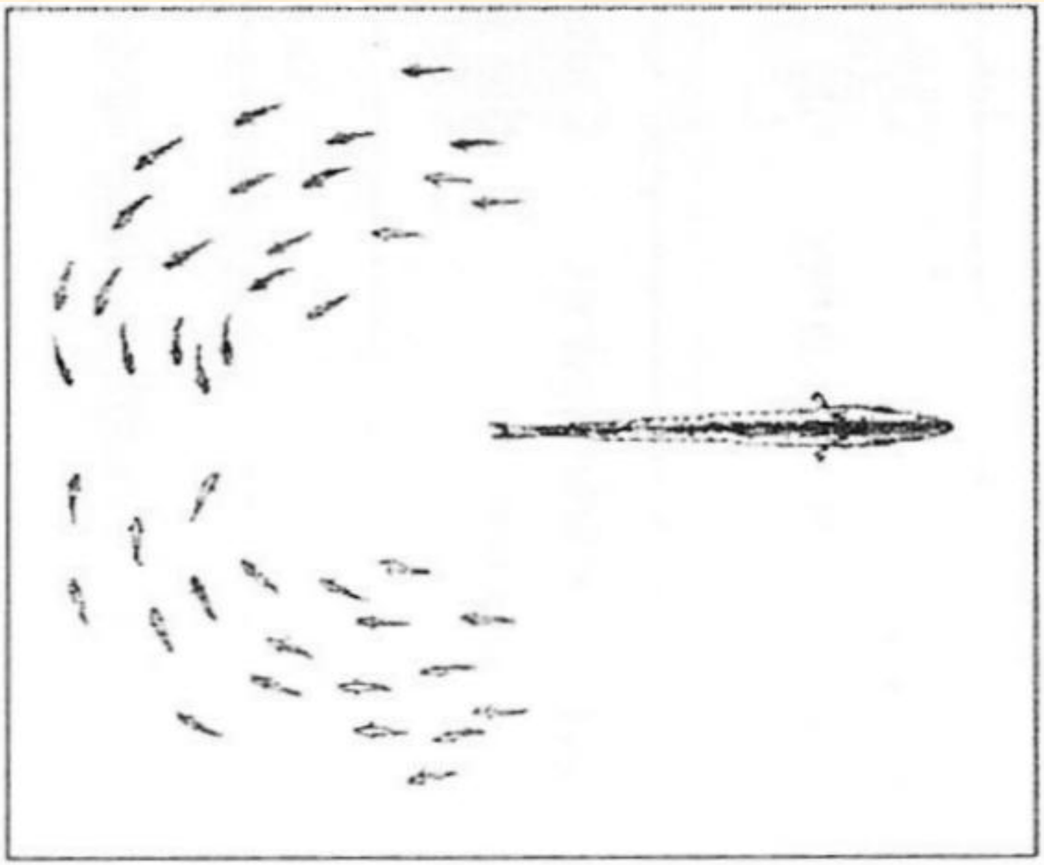


Fig. from Camazine & al., *Self-Org. Biol. Sys.*

Fountain Effect

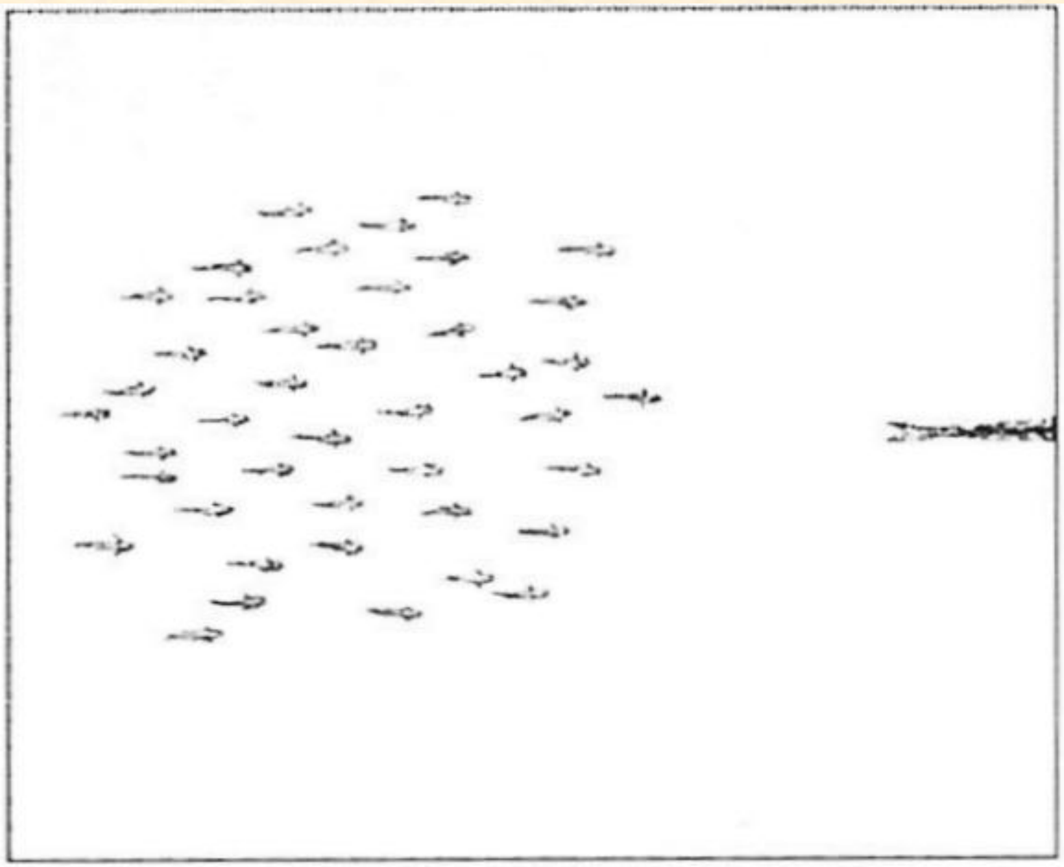


Fig. from Camazine & al., *Self-Org. Biol. Sys.*

Better Predation

- Coordinated movements to trap prey
  - e.g. parabolic formation of tuna
- More efficient predation
  - e.g., killer whales encircle dolphins
  - take turns eating

Other Efficiencies

- Fish schooling may increase hydrodynamic efficiency
  - endurance may be increased up to 6×
  - school acts like "group-level vehicle"
- V-formation increases efficiency of geese
  - range 70% greater than that of individual
- Lobsters line up single file by touch
  - move 40% faster than when isolated
  - decreased hydrodynamic drag

Characteristic Arrangement of School

- Shape is characteristic of species
- Fish have preferred distance, elevation & bearing relative to neighbors
- Fish avoid coming within a certain minimum distance
  - closer in larger schools
  - closer in faster moving schools

Alternatives to Self-Organization

- “Templates”
  - no evidence that water currents, light, chemicals guide collective movement
- “Leaders”
  - no evidence for leaders
  - those in front may drop behind
  - those on flank may find selves in front
  - each adjusts to *several* neighbors
- “Blueprint” or “Recipe”
  - implausible for coordination of large schools
  - e.g., millions of herring, hundreds of millions of cod

Self-Organization Hypothesis

- Simple attraction & repulsion rules generate schooling behavior
  - *positive feedback*: brings individuals together
  - *negative feedback*: but not too close
- Rules rely on local information
  - i.e. positions & headings of a few nearby fish
  - no global plan or centralized leader

Mechanisms of Individual Coordination

- Vision
  - governs *attraction*
  - & *alignment*
- Lateral line
  - sensitive to water movement
  - provides information on speed & direction of neighbors
  - governs *repulsion*
  - & *speed matching*
- How is this information integrated into a behavioral plan?
  - most sensitive to *nearest neighbors*

Basic Assumptions of Huth & Wissel (1992) Model

- All fish follow same rules
- Each uses some sort of weighted average of positions & orientations of nearest neighbors
- Fish respond to neighbors probabilistically
  - imperfect information gathering
  - imperfect execution of actions
- No external influences affect fish
  - e.g. no water currents, obstacles, …

Ranges of Behavior Patterns

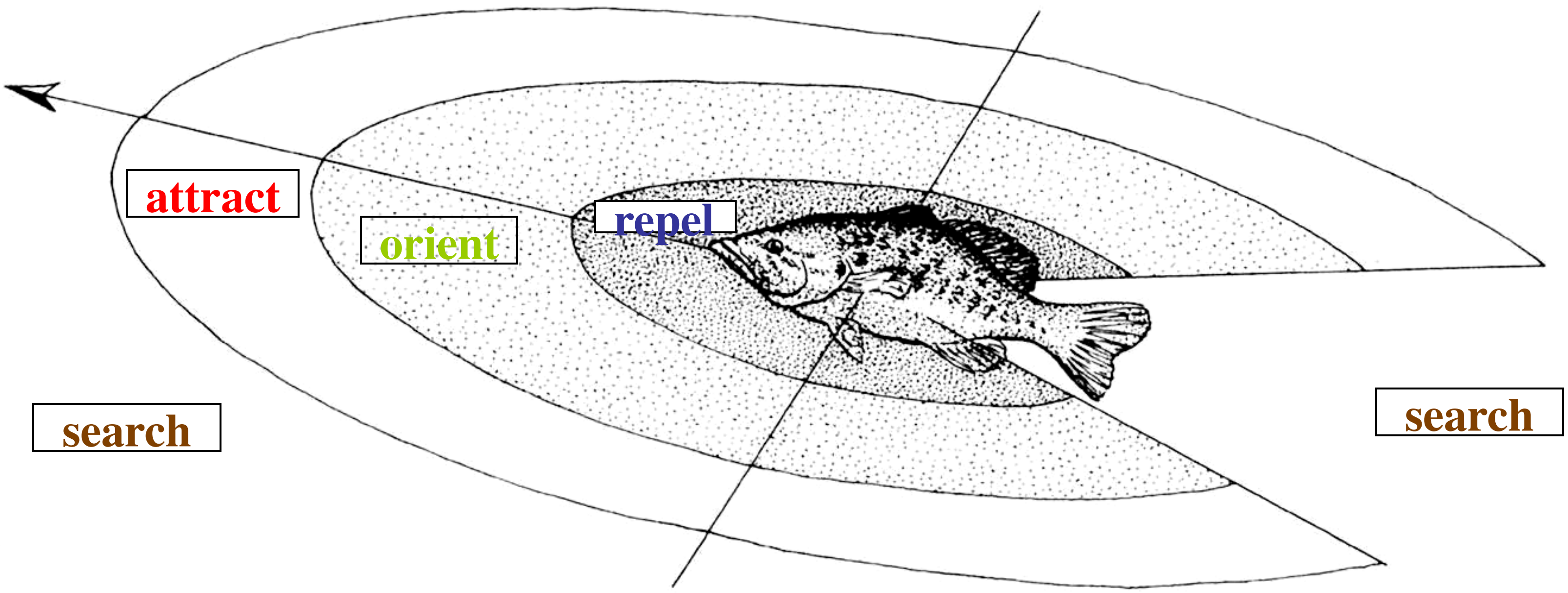


Fig. adapted from Camazine & al., *Self-Org. Biol. Sys.*

Model Behavior of Individual

1. Determine a target direction from each of three nearest neighbors:

   if in *repel range*, **then** 180° + direction to neighbor

   else if in *orient range*, **then** heading of neighbor

   else if in *attract range*, **then**

   accelerate **if** ahead, decelerate **if** behind;

   return direction to neighbor

   else return our own current heading
2. Determine overall target direc. as average of 3 neighbors inversely weighted by their distances
3. Turn a fraction in this direction (determined by *flexibility*) + some randomness

Demonstration of NetLogo Simulation of Flocking/ Schooling

based on Huth & Wissel Model

Run Flock.nlogo

Limitations of Model

- Model addresses only motion in absence of external influences
- Ignores obstacle avoidance
- Ignores avoidance behaviors such as:
  - flash expansion
  - fountain effect
- Recent work (since 1997) has addressed some of these issues

“Boids”

A model of flocks, herds, and similar cases of coordinated animal motion by Craig Reynolds (1986)

NetLogo Simulation

- Flockmates are those within "vision"
- If nearest flockmate < minimum separation, turn away
- Else:
  - align with average heading of flockmates
  - cohere by turning toward average flockmate direction
- All turns limited specified maxima
- Note fluid behavior from deterministic rules

Demonstration of boids

Run Flocking.nlogo

Demonstration of boids (with 3D perspective)

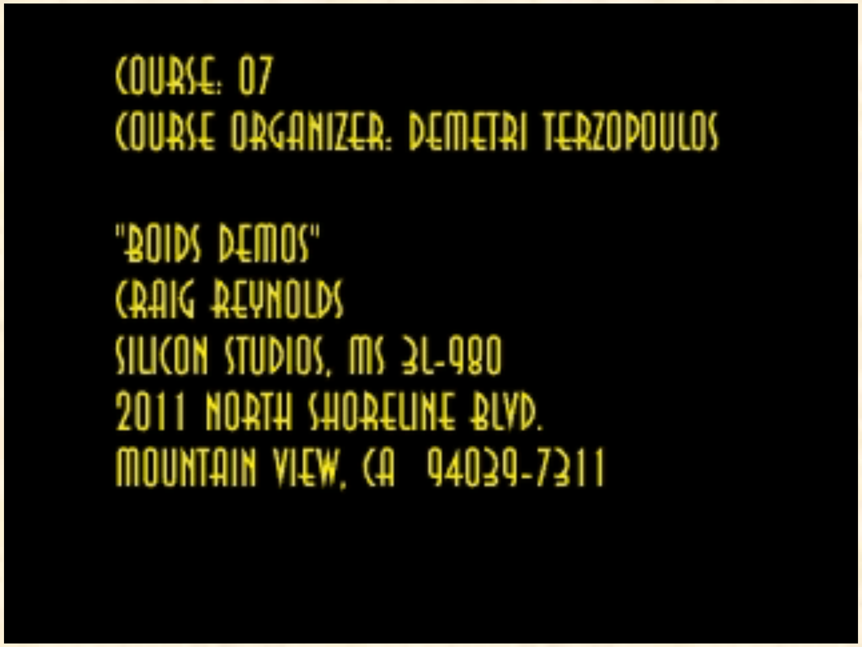
Run Flocking (Perspective Demo).nlogo

Demonstration of 3D boids

[Run Flocking 3D.nlogo]

Obstacle Avoidance

- Boid flock avoiding cylindrical obstacles (Reynolds 1986)
- This model incorporates:
  - predictive obstacle avoidance
  - goal seeking (scripted path)



Jon Klein's Flocking Algorithm

- Sight limited by "vision"
- Balances 6 "urges":
  - be near center of flock
  - have same velocity as flockmates
  - keep spacing correct
  - avoid collisions with obstacles
  - be near center of world
  - wander throughout world
- Strength of urge affects acceleration

Demonstration of Klein's Flocking Algorithm

Run Flocking 3D Alternate.nlogo

Use in Computer Animation

- Extract from *Stanley and Stella in "Breaking the Ice"* (1987)
- store.yahoo.com/odyssey3d/comanclascli2.html

Particle Swarm Optimization

(Kennedy & Eberhart, 1995)

Motivation

- Originally a model of social information sharing
- Abstract vs. concrete spaces
  - cannot occupy same locations in concrete space
  - can in abstract space (two individuals can have same idea)
- Global optimum (& perhaps many suboptima)
- Combines:
  - private knowledge (best solution each has found)
  - public knowledge (best solution entire group has found)

Particle Swarms

Idea

- moving points in the search space, which refine their knowledge by interaction

What is a particle?

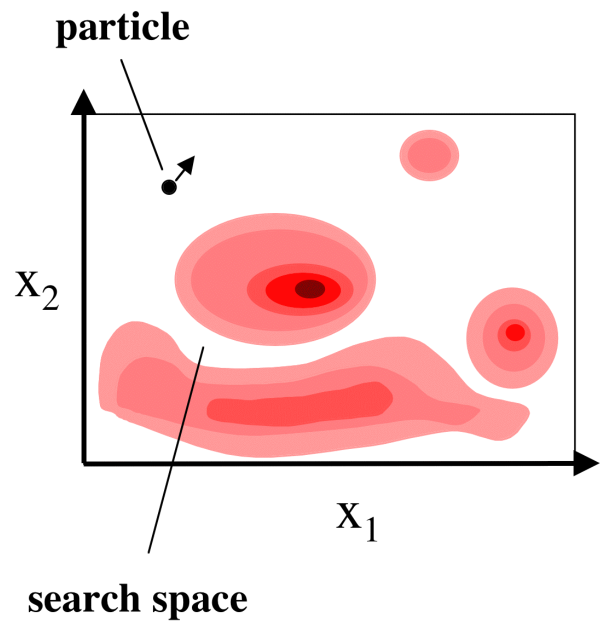
- a particle consists of:

  $\vec{x}_i$ position

  $\vec{v}_i$ velocity

  $\vec{p}_i$ best position found so far

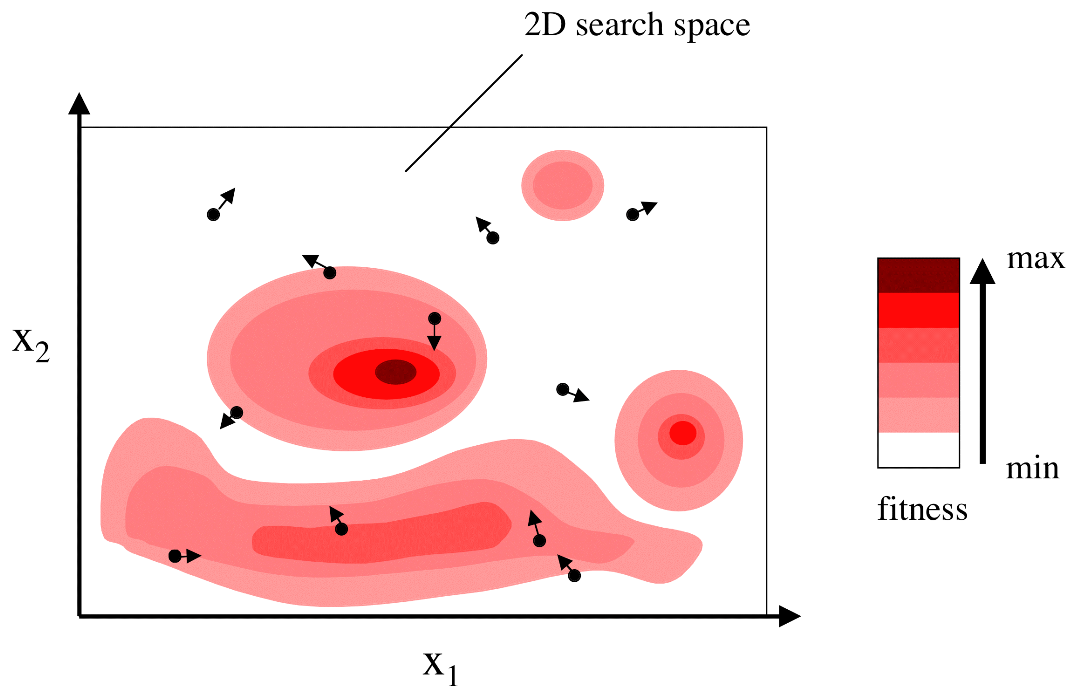
  velocity and position update rules



(Kennedy and Eberhart, 1995)

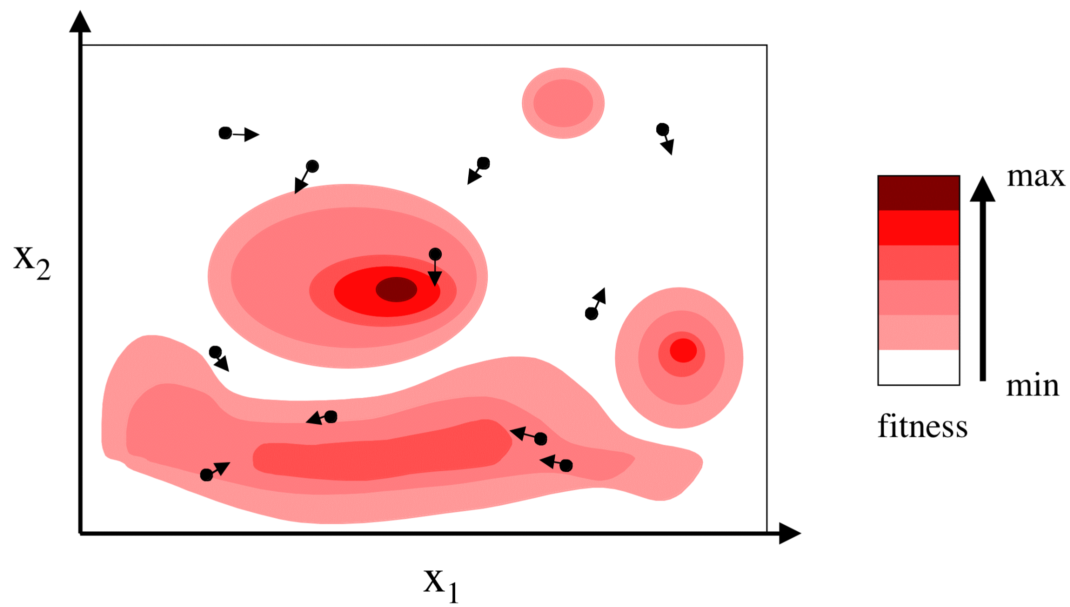
Example

Particle Swarms



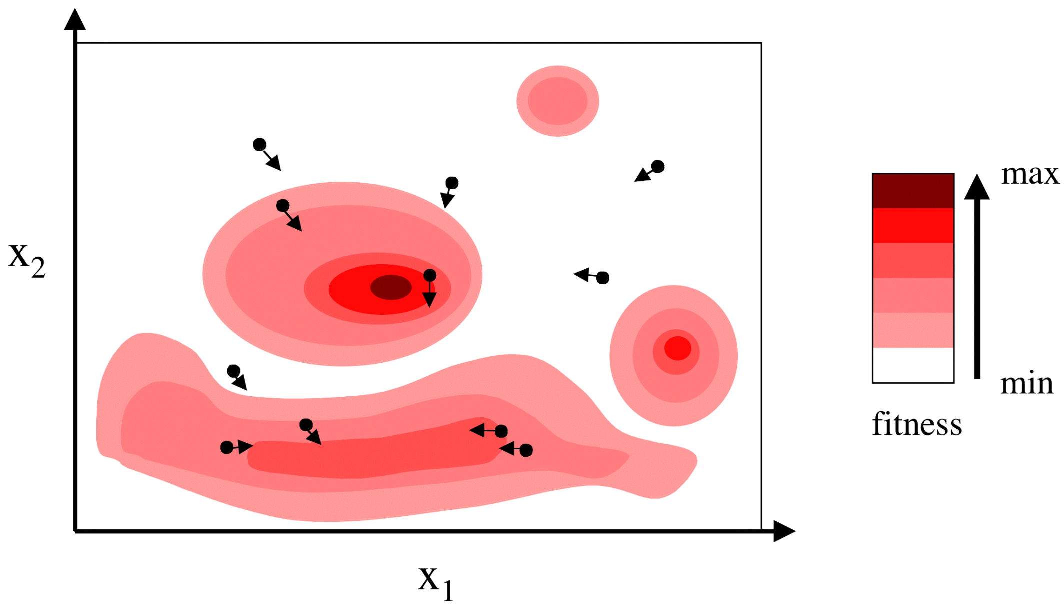
Example

Particle Swarms



Example

Particle Swarms



Example

Particle Swarms

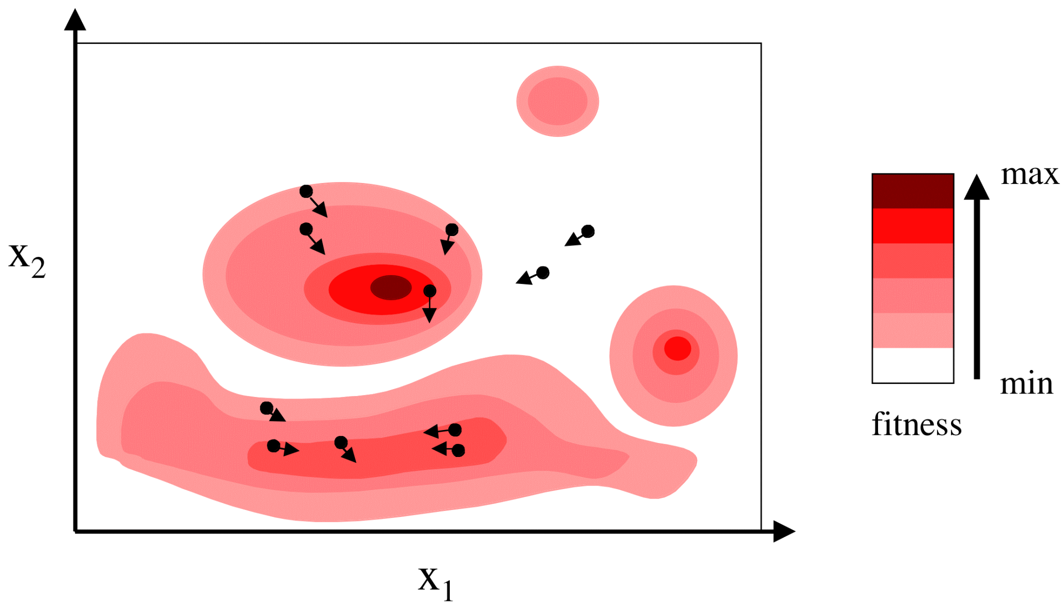


Fig. from EVALife site

Example

Particle Swarms

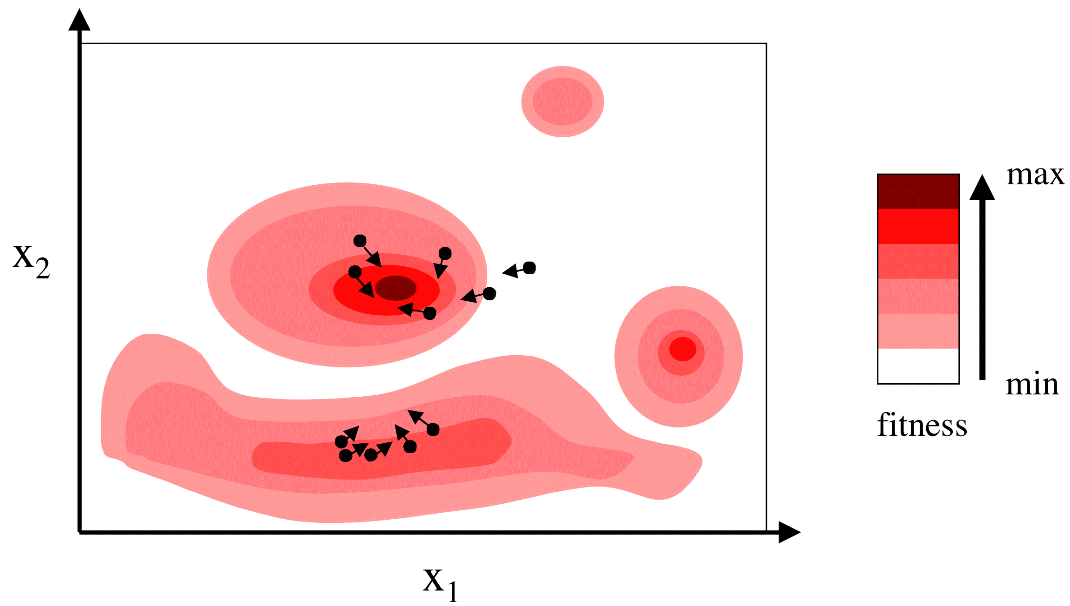


Fig. from EVALife site

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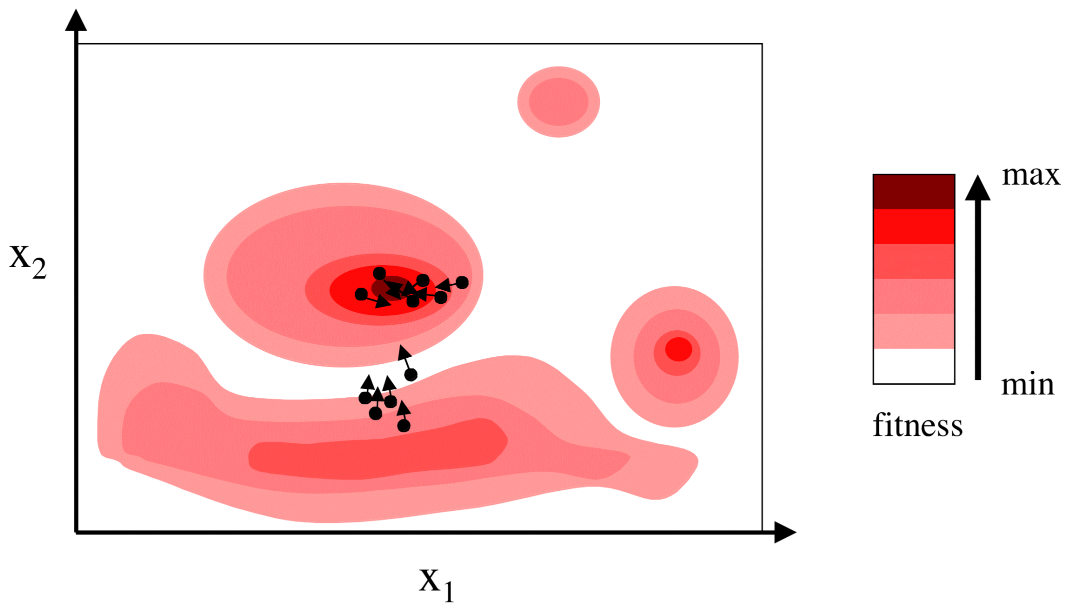
Particle Swarms



Example

Particle Swarms

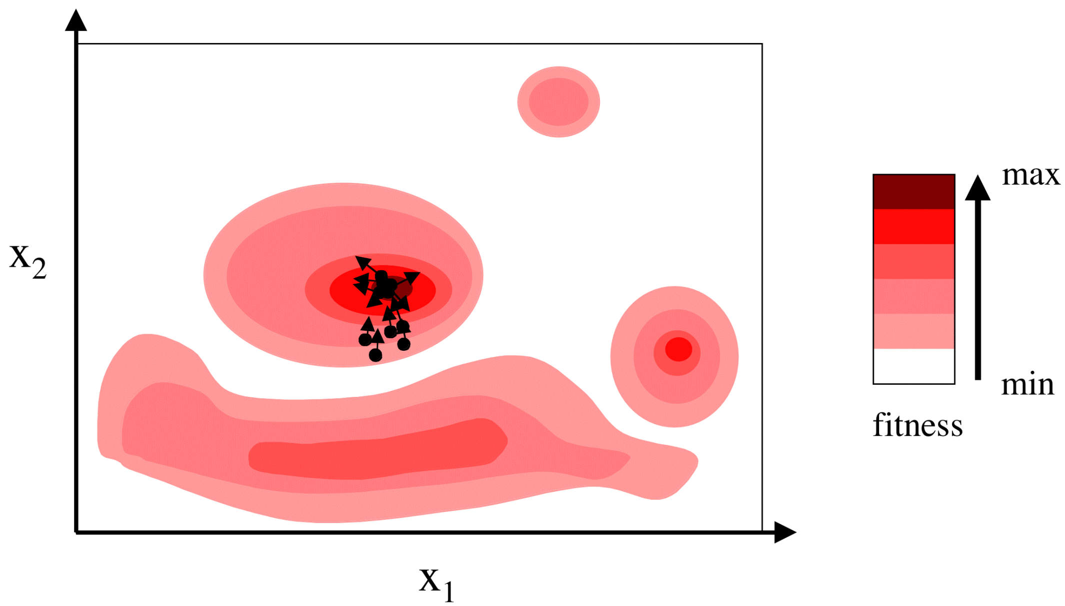


Fig. from EVALife site

Example

Particle Swarms

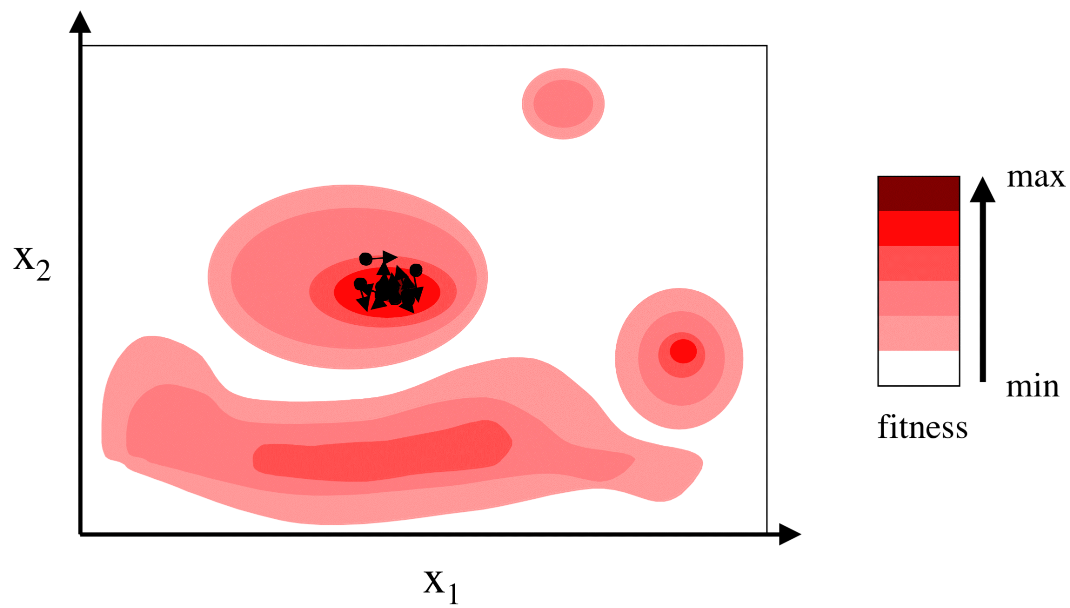


Fig. from EVALife site

Variables

$\mathbf{x}_k$ = current position of particle k

$\mathbf{v}_k$ = current velocity of particle k

$\mathbf{p}_k$ = best position found by particle k

$Q(\mathbf{x})$ = quality of position $\mathbf{x}$

g = index of best position found so far

i.e., $g = \text{argmax}_k\, Q(\mathbf{p}_k)$

ϕ_1, ϕ_2 = random variables uniformly distributed over [0, 2]

w = inertia < 1

Velocity & Position Updating

$\mathbf{v}_k' = w\,\mathbf{v}_k + \phi_1\,(\mathbf{p}_k - \mathbf{x}_k) + \phi_2\,(\mathbf{p}_g - \mathbf{x}_k)$

- $w\,\mathbf{v}_k$ maintains direction (*inertial* part)
- $\phi_1\,(\mathbf{p}_k - \mathbf{x}_k)$ turns toward private best (*cognition* part)
- $\phi_2\,(\mathbf{p}_g - \mathbf{x}_k)$ turns towards public best (*social* part)

$\mathbf{x}_k' = \mathbf{x}_k + \mathbf{v}_k'$

- Allowing $\phi_1, \phi_2 > 1$ permits overshooting and better exploration (*important!*)
- Good balance of *exploration* & *exploitation*
- Limiting $\|\mathbf{v}_k\| < \|\mathbf{v}_{\max}\|$ controls resolution of search

Netlogo Demonstration of Particle Swarm Optimization

Run PSO.nlogo

or Particle Swarm Optimization.nlogo

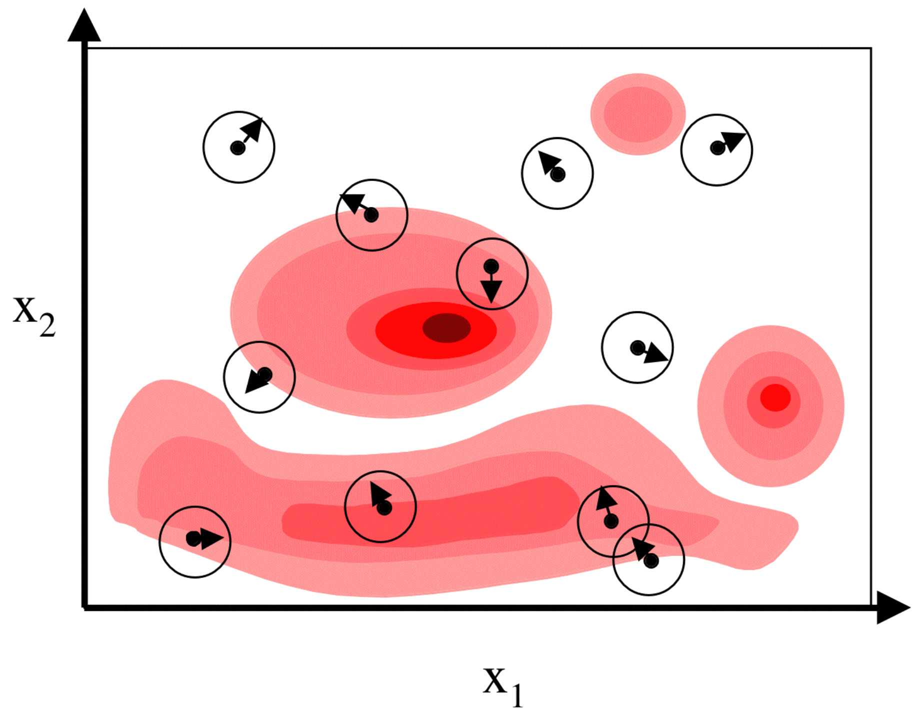
Yuhui Shi's Demonstration of Particle Swarm Optimization

Run www.engr.iupui.edu/~shi/PSO/AppletGUI.html

Improvements

- Alternative velocity update equation:
  $\mathbf{v}_k' = \chi\,[w\,\mathbf{v}_k + \phi_1\,(\mathbf{p}_k - \mathbf{x}_k) + \phi_2\,(\mathbf{p}_g - \mathbf{x}_k)]$
  χ = constriction coefficient (controls magnitude of $\mathbf{v}_k$)
- Alternative neighbor relations:
  - **spatial**: limited interaction range
  - **star**: fully connected (each responds to best of all others; fast information flow)
  - **circle**: connected to K immediate neighbors (slows information flow)
  - **wheel**: connected to one axis particle (moderate information flow)

Spatial Extension



- Spatial extension avoids premature convergence
- Preserves diversity in population
- More like flocking/schooling models

Netlogo Demonstration of Particle Swarm Optimization with Collision Avoidance

Run PSO.nlogo

Some Applications of PSO

- integer programming
- minimax problems
  - in optimal control
  - engineering design
  - discrete optimization
  - Chebyshev approximation
  - game theory
- multiobjective optimization
- hydrologic problems
- musical improvisation!

Millonas' Five Basic Principles of Swarm Intelligence

1. *Proximity principle:*

   pop. should perform simple space & time computations

2. *Quality principle:*

   pop. should respond to quality factors in environment

3. *Principle of diverse response:*

   pop. should not commit to overly narrow channels

4. *Principle of stability:*

   pop. should not change behavior every time env. changes

5. *Principle of adaptability:*

   pop. should change behavior when it's worth comp. price

(Millonas 1994)

Kennedy & Eberhart on PSO

"This algorithm belongs ideologically to that philosophical school

that allows wisdom to emerge rather than trying to impose it,

that emulates nature rather than trying to control it,

and that seeks to make things simpler rather than more complex.

Once again nature has provided us with a technique for processing information that is at once elegant and versatile."

Additional Bibliography

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2. Bonabeau, E., Dorigo, M., & Theraulaz, G. *Swarm Intelligence: From Natural to Artificial Systems*. Oxford, 1999, chs. 2, 6.
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4. Resnick, M. *Turtles, Termites, and Traffic Jams: Explorations in Massively Parallel Microworlds*. MIT Press, 1994, pp. 59-68, 75-81.
5. Kennedy, J., & Eberhart, R. "Particle Swarm Optimization," *Proc. IEEE Int'l. Conf. Neural Networks* (Perth, Australia), 1995. http://www.engr.iupui.edu/~shi/pso.html.

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