Swarming: Collective Behavior, Foraging and Optimization

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Swarming

Dumb parts, properly connected into a swarm, yield smart results.

Kevin Kelly
Swarming

Great!
Swarming

Great! but how do you properly connect the parts?
Social insects do it
From social insects to ... artificial insects!
A social insect colony is...

- **Flexible**: the colony can respond to internal perturbations and external challenges
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- **Flexible**: the colony can respond to internal perturbations and external challenges
- **Robust**: tasks are completed even if some individuals fail
- **Decentralized**: there is no central control(ler) in the colony
- **Self-organized**: paths to solutions are emergent rather than predefined
Swarm Intelligence ...

- is a mindset rather than a technology,
- is a bottom-up approach to controlling and optimizing distributed systems,
- using resilient, decentralized, self-organized techniques,
- initially inspired by how social insects operate - shaped by millions of years of evolution.
1. Collective behavior
Swarm lesson 1: complexity from simple rules

- **Network 1**: pick a protector and an aggressor, then move so that your protector is always located between you and your aggressor.
Swarm lesson 1: complexity from simple rules

- **Network 1**: pick a protector and an aggressor, then move so that your protector is always located between you and your aggressor.

- **Network 2**: pick a protected and an aggressor, then move so as to be always located between your protected and his/her aggressor.
Swarm lesson 1: complexity from simple rules

you protector aggressor

protected you aggressor
Bad:

- Difficult to predict collective behavior from individual rules.
- Interrogate one of the participants, it won’t tell you anything about the function of the group.
- Small changes in rules lead to different group-level behavior.
- Individual behavior looks like noise: how do you detect threats?
Bad:
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Good:
- Possible to efficiently control organization or manipulate groups using simple rules.
- Possible to predict group-level outcome using bottom simulation.
Simple rules at Southwest Airlines

Problem
- Optimize cargo routing
- Use simple rules

Results
- 71% improvement
- At least $10m/yr
Particle Swarm optimisation

PSO invented by Russ Eberhart (engineering Prof.) and James Kennedy (social scientist)
Cooperation Example
Basic Idea

- Each particle is searching for the optimum
- Each particle is moving and hence has a velocity.
- Each particle remembers the position it was in where it had its best result so far (its personal best)
- But this would not be much good on its own; particles need help in figuring out where to search.
Basic Idea

- The particles in the swarm co-operate. They exchange information about what they’ve discovered in the places they have visited.
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- The particles in the swarm co-operate. They exchange information about what they’ve discovered in the places they have visited.
- The co-operation is very simple. In basic PSO it is:
  - A particle has a neighbourhood associated with it.
  - A particle knows the fitnesses of those in its neighbourhood, and uses the position of the one with best fitness.
  - This position is simply used to adjust the particle’s velocity.
Initialization | Positions and velocities
What a particle does

- In each timestep, a particle has to move to a new position. It does this by adjusting its velocity. The adjustment is essentially this:
  - The current velocity PLUS
  - A weighted random portion in the direction of its personal best PLUS
  - A weighted random portion in the direction of the neighbourhood best.
- Having worked out a new velocity, its position is simply its old position plus the new velocity.
Neighbourhoods

general social
Neighbourhoods
The circular neighbourhood

Particle 1’s 3-neighbourhood

Virtual circle
Particles adjust their positions according to a “Psychosocial compromise” between what an individual is comfortable with, and what society reckons.
What a particle does

- Equation (a)
  \[ v[] = c_0 \cdot v[] + c_1 \cdot \text{rand}() \cdot (pbest[] - \text{present}[]) + c_2 \cdot \text{rand}() \cdot (gbest[] - \text{present}[]) \]

- (In the original method, \( c_0 = 1 \) (inertial coefficient), but many researchers now play with this parameter)
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- Equation (a)
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- Equation (b)
  \[ \text{present}[] = \text{present}[] + v[] \]
  new position = old position + velocity
For each particle
  - Initialize particle

END
For each particle
  ▶ Initialize particle

END

Do
  ▶ For each particle
    ▶ Calculate fitness value
    ▶ If the fitness value is better than its personal best set current value as the new pBest
  ▶ End

While maximum iterations or minimum error criteria is not attained
For each particle
  ▶ Initialize particle

END

Do

For each particle
  ▶ Calculate fitness value
  ▶ If the fitness value is better than its personal best set current value as the new pBest

End

Choose the particle with the best fitness value of all as gBest

For each particle
  ▶ Calculate particle velocity according equation (a)
  ▶ Update particle position according equation (b)

End

While maximum iterations or minimum error criteria is not attained
Parameters

- Particles’ velocities on each dimension are clamped to a maximum velocity $V_{\text{max}}$.
- If the sum of accelerations would cause the velocity on that dimension to exceed $V_{\text{max}}$, then the velocity on that dimension is limited to $V_{\text{max}}$.
- $V_{\text{max}}$ is a parameter specified by the user.
Parameters

- Number of particles (swarm size)
- $C_1$ (importance of personal best)
- $C_2$ (importance of neighbourhood best)
- $V_{\text{max}}$: limit on velocity
Explore PSO and its parameters with the app at http://www.macs.hw.ac.uk/~dwcorne/mypages/apps/pso.html