

# Metaheuristic Optimization: Particle Swarm Optimization (PSO)

Adaptive and Cooperative Algorithms (ECE 457A)

ECE, MME, and MSCI Departments,  
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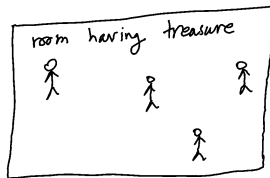
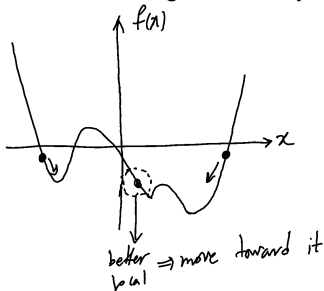
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# Swarm Optimization: the Idea

- Some of the metaheuristic optimization algorithms are swarm optimization methods.
- In swarm methods, we have a swarm of particles which collaboratively try to find the global best in an optimization landscape.
- The swarm methods are usually (but not always) bio-inspired or nature-inspired algorithms where the particles behave like animals, birds, creatures, etc.
- A recent survey on nature-inspired optimization is published in 2023 [1].
- For example, a swarm method can be inspired by a flock of birds or group of fish.
- Many bio-inspired or swarm metaheuristic algorithms exist such as:
  - ▶ Particle Swarm Optimization (PSO): 1995 [2]
  - ▶ Ant colony: 1996 [3, 4]
  - ▶ Grey wolf optimizer: 2014 [5]
  - ▶ Whale optimization algorithm: 2016 [6]
  - ▶ Salp Swarm Algorithm: 2017 [7]
  - ▶ A scholar in this area: Seyedali Mirjalili, Torrens University Australia, Australia, <https://scholar.google.com/citations?user=TJHmrREAAAJ&hl=en&oi=sra>

# Particle Swarm Optimization: the Idea

- Particle Swarm Optimization (PSO) was proposed in 1995 [2].
- The idea of PSO is like finding a treasure by a group of people.



- It is inspired a flock of birds or group of fish. Hence, it can be seen as one of the bio-inspired metaheuristic algorithms or swarm optimization.

# Particle Swarm Optimization: the Formula

- The candidate solutions are the particles (vectors).
- Every particle searches locally in a local neighborhood.
- Three components for the velocity vector for updating the solution:
  - ▶ the momentum (history) of previous velocity (fro exploitation):  $\alpha_1 \mathbf{v}_i^{(k)}$
  - ▶ update according to the local best in the iteration:  $\alpha_2 (\mathbf{x}_{\text{localBest}}^{(k)} - \mathbf{x}_i^{(k)})$
  - ▶ update according to the global best in the iteration:  $\alpha_3 (\mathbf{x}_{\text{globalBest}}^{(k)} - \mathbf{x}_i^{(k)})$
- The update of every particle:

$$\mathbf{v}_i^{(k+1)} := \alpha_1 \mathbf{v}_i^{(k)} + \alpha_2 (\mathbf{x}_{\text{localBest}}^{(k)} - \mathbf{x}_i^{(k)}) + \alpha_3 (\mathbf{x}_{\text{globalBest}}^{(k)} - \mathbf{x}_i^{(k)}), \quad (1)$$
$$\mathbf{x}_i^{(k+1)} := \mathbf{x}_i^{(k)} + \mathbf{v}_i^{(k+1)}. \quad (2)$$

where  $\alpha_1$ ,  $\alpha_2$ , and  $\alpha_3$  are weight (regularization) hyper-parameters.

- Variants of PSO:
  - ▶ local best:
    - ★ local best of particle itself in this iteration
    - ★ local best of particle itself so far (in all iterations until now)
  - ▶ global best:
    - ★ global best of all iterations so far (best found solution so far)
    - ★ best of solutions found by particles in this iteration

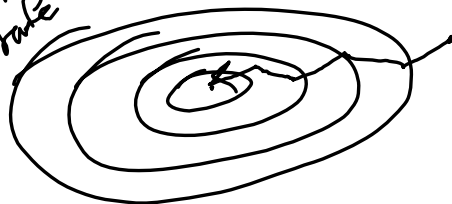
$$\begin{cases} V^{(k+1)} \leq V^{(k)} + \Delta V^{(k+1)} \\ \Delta V^{(k+1)} = -\eta \left( \frac{\partial V}{\partial W} \right) \rightarrow \text{gradient} \end{cases}$$

$$\Delta V^{(k+1)} =$$

$$-\eta \left( \frac{\partial V}{\partial W} \right) + \Delta V^{(k)}$$

learning rate

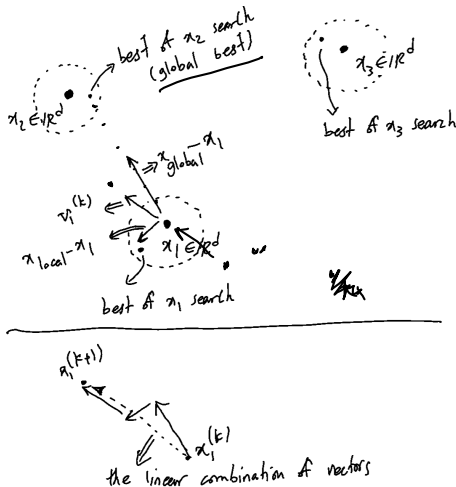
momentum rate



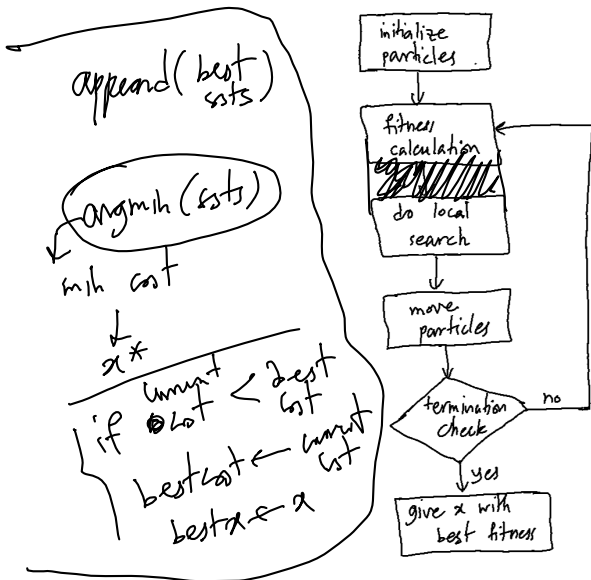
# Particle Swarm Optimization: Visualizing the Formula

$$\mathbf{v}_i^{(k+1)} := \alpha_1 \mathbf{v}_i^{(k)} + \alpha_2 (\mathbf{x}_{\text{localBest}}^{(k)} - \mathbf{x}_i^{(k)}) + \alpha_3 (\mathbf{x}_{\text{globalBest}}^{(k)} - \mathbf{x}_i^{(k)}),$$

$$\mathbf{x}_i^{(k+1)} := \mathbf{x}_i^{(k)} + \mathbf{v}_i^{(k+1)}.$$



# Particle Swarm Optimization: Flowchart



# Acknowledgment

- Some slides of this slide deck are inspired by teachings of Prof. Saeed Sharifian at the Amirkabir University of Technology, Department of Electrical Engineering.
- A good web link about PSO: <https://www.analyticsvidhya.com/blog/2021/10/an-introduction-to-particle-swarm-optimization-algorithm/>



# References

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