ปัญญารวมฝูง

Swarm Intelligence: From Natural to Artificial Systems

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อยากได้ final state ที่เป็นตามเงื่อนไข เช่น Hill climbing

Introduction

- What is swarm intelligence ?

  ไม่ซ.ด. ซับซ้อน ฉลาด
  เอามาลงทำด้วยกัน

  "Swarm Intelligence (SI) is the property of a system whereby the collective behaviors of (unsophisticated) agents interacting locally with their environment cause coherent functional global patterns to emerge." ย้ำว่าเป็นการเอา agent หลายตัวทำงานร่วมกัน
  แต่ละ interact ตัวเองกับสิ่งแวดล้อมกับ agent อื่น อาจจะไม่ได้ค่า solution
  แต่เอาทุกคนรวมกันเป็น global solution

- "SI provides a basis with which it is possible to explore collective (or distributed) problem solving without centralized control or the provision of a global model."

  (http://dsp.jpl.nasa.gov/members/payman/swarm/)

Some natural Swarm Intelligence systems

- **Ants**
  - find the **shortest path** to food มด 1 ตัวหา path ไม่ได้ แต่ 1 ฝูงไปได้
  - make **cemeteries** ทำรังมด
  - **sort** their brood by size เอาไข่มาเรียงตามขนาด
  - etc.

- **Termites**
  - **build nests** with complex features like
    - fortified chambers
    - spiral air vents
    - fungus gardens
    - etc.

- **Bees** หาแหล่งอาหารที่ใกล้สุด
  - gather pollen with high efficiency, exploiting the **nearest richest food source first**.

- **Geese**
  - **coordinate** takeoff and landing
  - flight **patterns**
  - etc.

- **Fish / Birds /…**
  - swarms

How Do Social Insects Coordinate Their Behaviour?

- communication is necessary การสื่อสารนั้นสำคัญ
- two types of communication
  - direct agent – agent เอาหนวดมดแตะกันเพื่อแลกเปลี่ยน
    - antennation, trophallaxis (food or liquid exchange), mandibular contact, visual contact, chemical contact, etc.
  - indirect
    - two individuals interact indirectly when one of them modifies the environment and the other responds to the new environment at a later time

      called **stigmergy** mark ทิ้งไว้ที่ env เมื่อตัวอื่นมอง

      สัตว์จะทำตามสิ่งที่เห็น

Stigmergy

- "La coordination des taches, la regulation des constructions ne dependent pas directement des oeuvriers, mais des constructions elles-memes. ***L'ouvrier ne dirige pas son travail, il est guidé par lui***. C'est à cette stimulation d'un type particulier que nous donnons le nom du **STIGMERGIE** (*stigma*, piqure; *ergon*, travail, oeuvre = oeuvre stimulante)." Grassé P. P., 1959

- ["The coordination of tasks and the regulation of constructions does not depend directly on the workers, but on the constructions themselves. ***The worker does not direct his work, but is guided by it***. It is to this special form of stimulation that we give the name **STIGMERGY** (*stigma*, sting; *ergon*, work, product of labour = stimulating product of labour)."]

เราจะสร้างบ้านร่วมกัน ดูผลลัพธ์ ณ ขณะๆ กัน

เราตอบกระทำต่อสิ่งแวดล้อมที่เปลี่ยนไป

Stigmergy

Communication through marks in the environment …

- Marks serve as a shared memory for the agents ต้อง mak ไว้
- Promotes loose coupling
- Robust

Stigmergy ~ action + sign:

- Agents put marks in the environment (inform other agents about issues of interest)
- other agents perceive these marks (influence their behavior)
- manipulate marks
- other agents perceive the marks
- etc.

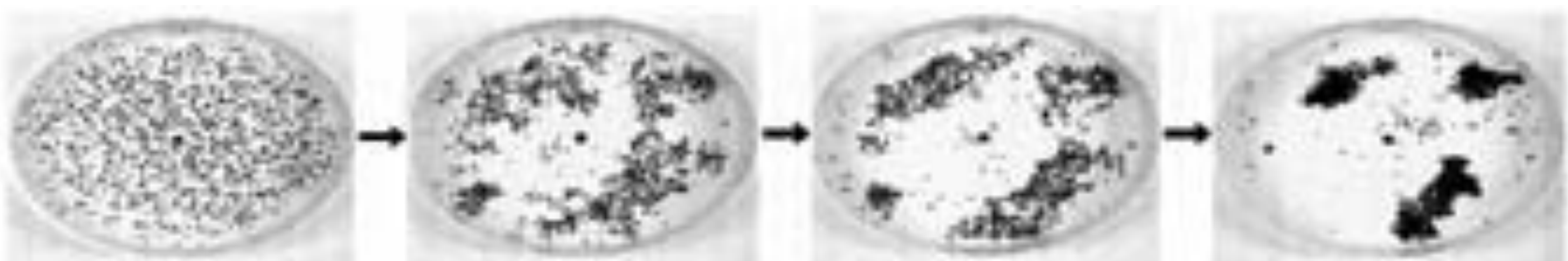
Marks can be

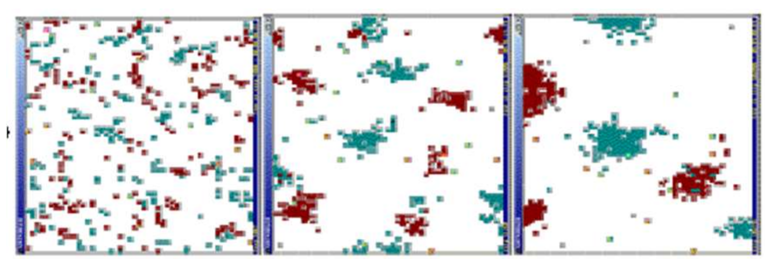
- static (environment does not manipulate marks over time)
  - e.g., flags เปลี่ยนแล้วเปลี่ยนเลย
- dynamic (environment manipulates marks over time)
  - e.g., pheromones, gradient fields ราดปัสสาวะเดิม ระเหยตามเวลา

Example of Stigmergy: Ant cemeteries in nature

- simple behaviour rules for ants
  - wander around

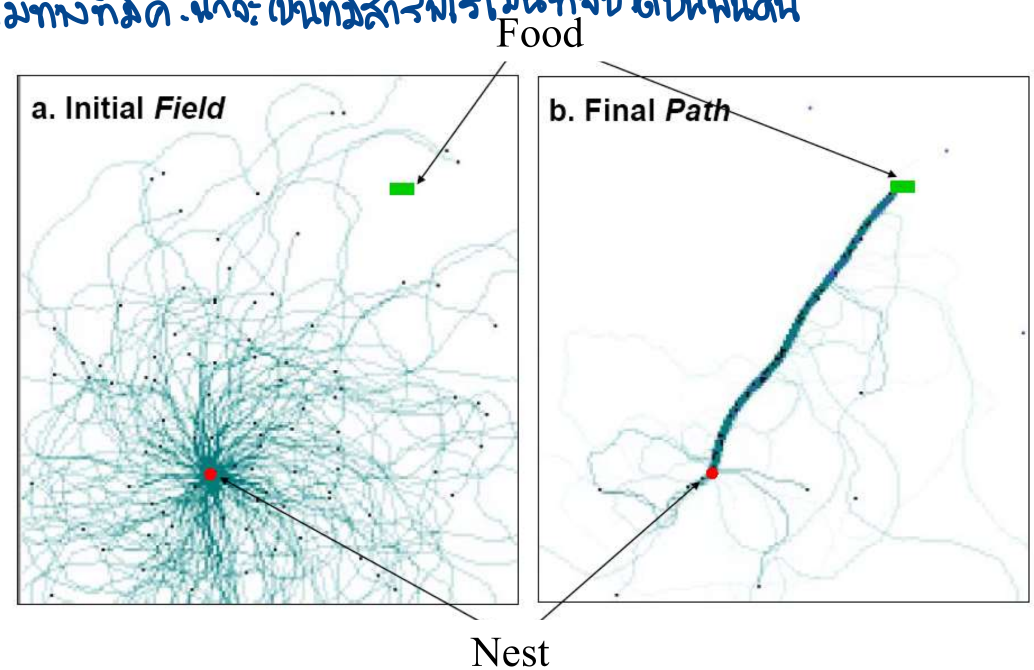
  - if you find a dead ant
    pick it up with probability inversely proportional
    to the number of other dead ants nearby
  - if you are carrying a dead ant
    put it down with probability directly proportional
    to the number of other dead ants nearby





Example of Stigmergy: Trail Following and Ants Foraging Behaviour

- while walking, ants and termites
  - may deposit a pheromone on the ground ปล่อยสารฟีโรโมนบนพื้นดิน
  - follow with high probability pheromone trails they sense on the ground เดินตามทางที่สุด .น่าจะเป็นที่มีสารฟีโรโมนที่จับได้บนพื้นดิน



“Artificial” Stigmergy

***Indirect communication** mediated by modifications of environmental states which are only **locally accessible** by the communicating agents*

Dorigo & Di Caro, 1999

- **Characteristics of artificial stigmergy:**
  - **Indirect communication**
  - **Local accessibility**

Foraging Strategies in Ants

- The Binary Bridge Experiment (Page 27)

  The ants choose one branch over the other due to some random fluctuations.

- Probability of choosing one branch over the other ~

$$P_A = \frac{(k + A_i)^n}{(k + A_i)^n + (k + B_i)^n} = 1 - P_B$$

- The values of k and n determined through experiments.

  k = degree of attraction of an unmarked branch

  n = choice function

Foraging Strategies in Ants

- Ants deposit pheromone on the paths that they cover and this results in the building of a solution (optimal path).

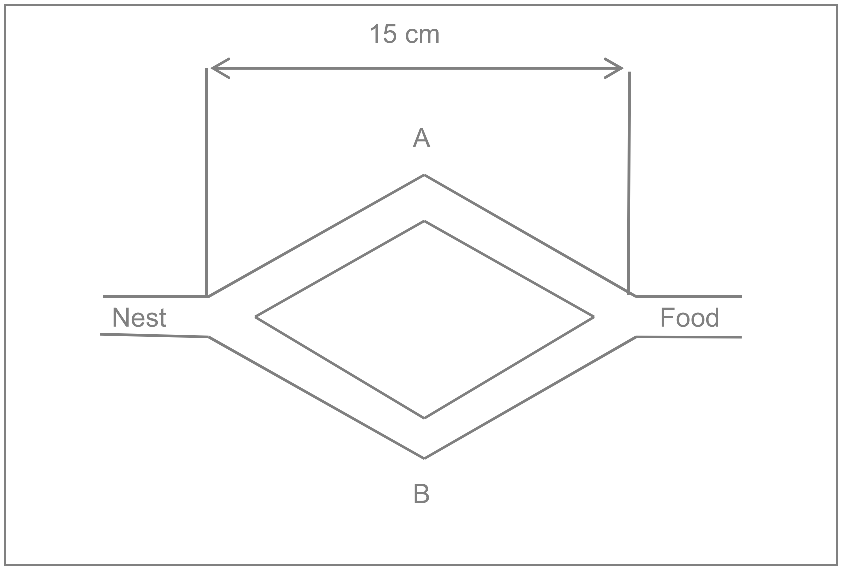
- In SI and optimization, concept of pheromone evaporation is used.
- Helps in avoiding suboptimal solutions – local optima.
- May differ from how it takes places in the real world.

Foraging Strategies in Ants

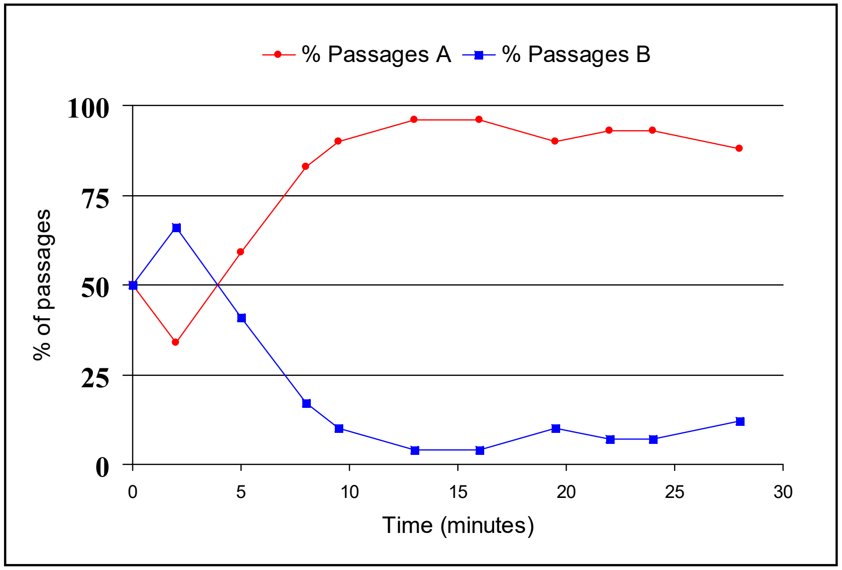
- Inter-nest Traffic studied – a case of natural optimization
- Similarity with MST shown by Aron et al.
- Other experiments done – effect of light vs dark, chemical vs visual cues.

- Conclusion here: some colonies have networks of nests several hundreds of meters in span – it is possible this is close to a MST.

Ants Foraging Behaviour
Example: The Double Bridge Experiment



Simple bridge



% of ant passages on the two branches

Goss et al., 1989, Deneubourg et al., 1990

Raid Patterns of Army Ants

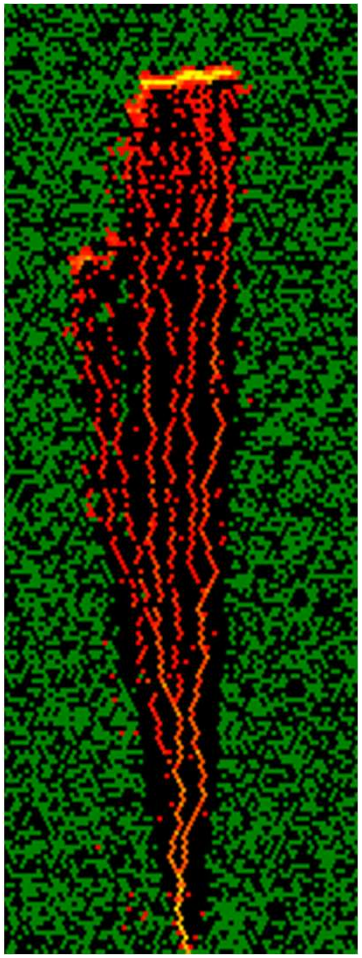
- An example of powerful, totally decentralized control.
- Example : Eciton burchelli can consist of as many as 200,000 workers.
- These individuals are blind, communication via pheromone.

Raid Patterns of Army Ants

- 3 species of ants have a common ancestor.
- Can the foraging behavior be explained through a different environment in each case?
- Deneubourg et al. modeled the behavior of these ants.
- Used a 2-D grid
- Had several rules like:
- 1 ant deposits 1 unit of pheromone per each visited site while returning to its nest.
- Maximum number of ants per site

Raid Patterns of Army Ants

- Pheromone disappearance rate at each site
- Movement of an ant from one site to the other based on a probabilistic mechanism shown earlier.
- Particular food distribution in the network
- A well-defined raid pattern is observed.
- Some similarity with the actual observations.



Ant Colony Optimization (ACO)

- We now come to more rigorous mathematical models.
- TSP has been a popular problem for the ACO models.

  - several reasons why TSP is chosen…..

- Key concepts:
- Positive feedback – build a solution using local solutions, by keeping good solutions in memory.
- Negative feedback – want to avoid premature convergence, evaporate the pheromone.
- Time scale – number of runs are also critical.

Ant System (AS)

- Used to solve TSP
- Transition from city i to j depends on:

1. Tabu list – list of cities not visited
2. Visibility = $1/d_{ij}$; represents local information – heuristic desirability to visit city j when in city i.
3. Pheromone trail $T_{ij}(t)$ for each edge – represents the learned desirability to visit city j when in city i.

ไปไหน visibility สูงสุด

ต้องการค่าสูง

ระยะทาง $i \to j$ มาก visit จะน้อย

- Generally, have several ants searching the solution space.

  m = n

Ant System (AS)

- Transition Rule
- Probability of ant k going from city i to j: สูตรความน่าจะเป็นที่มด$_k$ เดินจาก $i \rightarrow j$

$$p_{ij}^{k}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha} . \left[\eta_{ij}\right]^{\beta}}{\sum_{\ell \in J_i^k} \left[\tau_{il}(t)\right]^{\alpha} . \left[\eta_{il}\right]^{\beta}}$$

- Alpha and beta are adjustable parameters. like learning rate(α)

Pheromone update :

$$\Delta\tau_{ij}^{k} = Q / L^{k}(t) \quad if\ (i, j) \in T^{k}(t)\ else\ 0.$$

Ant System (AS)

ค่า update สารฟีโรโมนของมด

สูตรความน่าจะเป็นที่มด k เดินจาก i → j

$$p_{ij}^{k}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha} . \left[\eta_{ij}\right]^{\beta}}{\sum_{\ell \in J_i^k} \left[\tau_{il}(t)\right]^{\alpha} . \left[\eta_{il}\right]^{\beta}}$$

- Alpha = 0 : represents a greedy approach
- Beta = 0 : represents rapid selection of tours that may not be optimal.
- Thus, a tradeoff is necessary.

Ant System (AS)

- Pheromone update : การอัปเดตค่าสารฟีโรโมน

$$\Delta\tau_{ij}^{k} = Q / L^{k}(t) \quad if\ (i,j) \in T^{k}(t)\ else\ 0.$$

- T is the tour done at time t by ant k, L is the length, Q is a heuristic parameter.
- Pheromone decay:

$$\tau_{ij}(t) = (1-\rho).\tau_{ij}(t) + \Delta\tau_{ij}(t)$$

Ant System (AS)

- Modifications to the algorithm:
- Elitist scheme borrowed from GA
- Use the elitist to update its own tour (T+) edges for pheromone deposition.
- Could extend the same concept to "e" elitists ants.

- Results …..?
- Does not perform as well as other methods – the ones mentioned are TS (Tabu Search) and SA.

Ant System (AS)

- Does not converge to a single solution – is that a good criteria?

- However, they conclude that the "nonconvergence" property is interesting –

1. It tends to avoid trappings in local optima.
2. Could be used for dynamic problems.

- So next …..ACS

Ant Colony System (ACS)

$$j = \arg\max_{u \in J_k^i} \{[\tau_{ij}(t)].[\eta_{iu}]^{\beta}\} \; if \; q \leq q_o \quad j = J$$

- Modifications to AS.
- New transition rule:

  q_o is a parameter that can be tweaked
- It is similar to tuning temperature in SA.
- J is a city randomly selected according to the probability calculated previously.
- This helps ACS to improvise on the best solutions.

Ant Colony System (ACS)

$$\tau_{ij}(t) = (1-\rho).\tau_{ij}(t) + \rho.\Delta\tau_{ij}(t)$$

- Pheromone update rule (new):
- However, only applied to the best ant.
- The change in the pheromone concentration = 1/L+.

- Local updates done as follows:

$$\tau_{ij}(t) = (1-\rho).\tau_{ij}(t) + \rho\tau_0$$

Ant Colony System (ACS)

- To improves its search methodology, uses a candidate list of cl closest cities, considers these first, considers other cities only when the list is exhausted.
- Example cl = 15 on Page 51.

- ACS-TSP has been applied on problems of various sizes.
- ACS-TSP has been shown to be superior over other methods like GA, SA, EP for problems of size 50 – 100 cities.
- For larger size problems………

Ant Colony System (ACS)

- Use a local search method in conjunction with ACS-TSP.
- Called as 2-opt, 3-opt – refers to the number of edges exchanged iteratively to obtain a local optima.

- Has been shown to be comparable to the best techniques available (GA).

- Other methods for improvement-
- Elitism, worst tours (pheromone removed), local search enhancement.

The Quadratic Assignment Problem (QAP)

- Find pi such that the following is minimized:

$$C(\pi) = \sum_{i,j=1}^{n} d_{ij} f_{\pi(i)\pi(j)}$$

- QAP has shown to be NP-hard.
- d's are the distance between the nodes and f's are the flows between nodes.
- The problem is similar to TSP.
- distance potentials and flow potentials.

The Quadratic Assignment Problem

- Associate the minimum total flow at a node with the maximum total potential and so on : min-max coupling rule.
- This is a good heuristic, but does not give the optimal results.

- Hence AS-QAP proposed.
- The transition rule – the probability that the kth ant chooses activity j as the activity to assign to location i is:

$$p_{ij}^{k}(t) = \frac{\left[\tau_{ij}(t)\right]^{\alpha} . \left[\eta_{ij}\right]^{\beta}}{\sum_{\ell \in J_i^k} \left[\tau_{il}(t)\right]^{\alpha} . \left[\eta_{il}\right]^{\beta}}$$

The Quadratic Assignment Problem

$$\tau_{ij}(t) = (1-\rho).\tau_{ij}(t) + \Delta\tau_{ij}(t)$$

- Same pheromone update rule as AS-TSP.
- Here the change is equal to $Q/C^k(t)$ though – hence low coupling (C) value means a stronger pheromone trail.

- Results :
- GA, ES < AS-QAP < TS, SA

- Improvements…..

Hybrid Ant System (HAS)

- Departs radically from previously described ACO algorithms.
- Three procedures:

1. Pheromone-trail-based modification
2. Local search
3. Pheromone trail updating

…..kind of the same idea as ACS.

Hybrid Ant System (HAS - QAP)

$$p_{ij}^{k} = \frac{\tau_{i\pi^{k}(j)} + \tau_{j\pi^{k}(i)}}{\sum_{l=1}^{n} (\tau_{i\pi^{k}(l)} + \tau_{l\pi^{k}(i)})}$$

- Over here, each ant represents a solution like in GA, SA etc.
- It moves to another solution by applying R swaps.
- Example R = n/3.
- And the probability of moving from one point in solution space to the other is given above.

Hybrid Ant System (HAS - QAP)

- Local search:
- After a new solution is obtained, do a local search to get a lower point in solution space.
- This point may not necessarily be the local optima (why?)

- Pheromone-trail updating is done as follows:

$$\tau_{i\pi(i)}(t) = (1-\rho).\tau_{i\pi(i)}(t) + \Delta\tau_{i\pi(i)}(t)$$

- Here the change at each time step = 1/C(pi)+.

Hybrid Ant System (HAS - QAP)

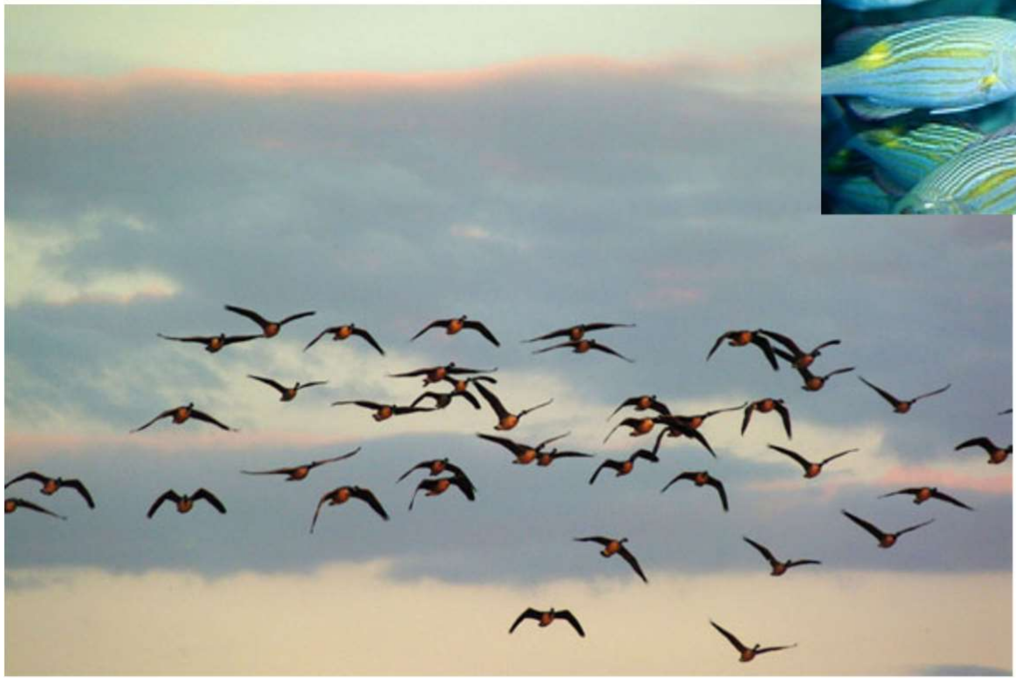
- Intensification – keeping new best solutions in memory and replacing the current ones with them; again similar to elitism.

- Diversification: All pheromone trail values are reinitialized if no improvement is made in S generations – example S = n/2.
- How does HAS-QAP perform ?
- The results are that it performs comparable to other methods.
- However, it does not do so well for regular problems – reason?
- Does good for problems that have a irregular structure.

Other applications of ACO

- ACO algorithms have been applied to several optimization problems now.
- Some of them are:
- Job-scheduling problem
- TSP
- Graph-coloring
- Vehicle Routing
- Shortest common supersequence

Particle Swarm Optimisation.



Particle Swarm Optimization

- Particle Swarm Optimization (PSO) mimics the collective intelligent behavior of " unintelligent " creatures.
- It was developed in 1995 by James Kennedy and Russell Eberhart [Kennedy, J. and Eberhart, R. (1995). "Particle Swarm Optimization", *Proceedings of the 1995 IEEE International Conference on Neural Networks*, pp. 1942-1948, IEEE Press.] (http://dsp.jpl.nasa.gov/members/payman/swarm/kennedy95-ijcnn.pdf)
- It has been applied successfully to a wide variety of search and optimization problems.
- In PSO, a swarm of *n* individuals communicate either directly or indirectly with one another in each search directions (gradients).

Particle Swarm Optimization
The Anatomy of a Particle

- A particle (individual) is composed of:
  - Three vectors:
    - The **x-vector** records the current position (location) of the particle in the search space,
    - The **p-vector** records the location of the best solution found so far by the particle, and
    - The **v-vector** contains a gradient (direction) for which particle will travel in if undisturbed.
  - Two fitness values:
    - The **x-fitness** records the fitness of the x-vector, and
    - The **p-fitness** records the fitness of the p-vector.

$$\mathbf{I}_{\mathbf{k}}$$

$$X = \langle x_{k0}, x_{k1}, \ldots, x_{kn-1} \rangle$$

$$P = \langle p_{k0}, p_{k1}, \ldots, p_{kn-1} \rangle$$

$$V = \langle v_{k0}, v_{k1}, \ldots, v_{kn-1} \rangle$$

x_fitness = ?

p_fitness = ?

Particle Swarm Optimization
Swarm search

Velocity calculation

$$v_{id(t)} = \omega v_{id(t-1)} + c_1 \times rand() \times \left(p_{id} - x_{id}\right) + c_2 \times Rand() \times \left(p_{gd} - x_{id}\right)$$

Position update

$$x_{id(t)} = x_{id(t-1)} + v_{id(t)}$$

x_{id} – current value of the dimension “d” of the dividual “i”
v_{id} – current velocity of the dimension “d” of the individual “i”.
P_{id} – optimal value of the dimension “d” of the individual “i” so far.
P_{gd} – current optimal value of the dimension “d” of the swarm.
c_1, c_2 – acceleration coefficients.
ω - inertia weight factor

Particle Swarm Optimization
Swarm Search

- In PSO, particles never die!
- Particles can be seen as simple agents that fly through the search space and record (and possibly communicate) the best solution that they have discovered.
- Initially the values of the velocity vectors are randomly generated with the range [-Vmax, Vmax] where Vmax is the maximum value that can be assigned to any v_{id}.
- Once the particle computes the new Xi and evaluates its new location. If x-fitness is better than p-fitness, then $P_i = X_i$ and p-fitness = x-fitness.

Particle Swarm Optimization
The algorithm

1. Initialise particles in the search space at random.
2. Assign random initial velocities for each particle.
3. Evaluate the fitness of each particle according a user defined objective function.
4. Calculate the new velocities for each particle.
5. Move the particles.
6. Repeat steps 3 to 5 until a predefined stopping criterion is satisfied.