Swarm Intelligence: From Natural to Artificial Systems

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Introduction

- What is swarm intelligence ?
  "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."
- "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/)

Chapter 2: Ant Foraging Behavior, Combinatorial Optimization, and Routing in Communications Network

- http://uk.geocities.com/markcsinclair/aco.html
- http://iridia.ulb.ac.be/~mdorigo/ACO/ACO.html
- http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/index.html

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

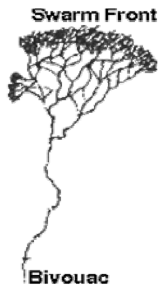
- Ants deposit pheromone on the paths that they cover and this results in the building of a solution (optimal path).
- In SI and optimization, concept of pheromone evaporation is used.
- Helps in avoiding suboptimal solutions – local optima.
- May differ from how it takes places in the real world.

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.

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.
- 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:

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

- Alpha and beta are adjustable parameters.

Ant System (AS)

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

- 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 :

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

- 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)

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

- 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:

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

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

Applications to networks

- These problems have their “states” changing with time.
- Routing in telecommunication networks is dynamic and distributed.

- Ant-based control (ABC) approach
- The ant’s goal is to build, and adapt to load changes as the system evolves.
- Example – a telephone network having bidirectional links; each node has k_i neighbors.
- Each node has certain constraints….

Ant-based control

- Each node has a capacity C_i and a spare capacity S_i.
- Each node has a routing table R_i – this table is update according to probability calculated from pheromone depositions. This is shown on Page 82.

- To calculate this, the concept of aging is involved – this means that an older ant has less influence on changes as compared to a younger ant. We want this since the conditions are changing – the nodes are receiving new calls.
- New ants are also generated from any node of the network at any time.

Ant-based control

- The objective here is to minimize the cost (Page 80).
- Schoonderwoerd et al. applied ABC to the British Telecom SDH network. (Page 88).
- ABC was shown to do better than other methods in terms of average number of call failures. (Page 87).

- Other modification to ABC
- ABC with smart ants – reinforce other paths with pheromone in addition to the main path.

Ant-based control

- Other methods that build upon ABC:
- ANTNET
- Ant Routing based on the Ant System (AS)

Conclusions

- Pro’s ?

- Con’s?