International Journal of Physical Sciences Volume 3, Number 2, 2008
 ISSN: 2006 – 1064

NATURE-INSPIRED OPTIMISATION METHODS: THE ANT ALGORITHM

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Abstract

Nature has inspired many optimization technique/methods. This paper is directed to introduce some of these methods to the reader and emphasis was laid on the Ant algorism by discussing its properties and what it entails. Also some of the problems that Ant algorism has been used to solve was listed while two of them were discussed in full; The TSP which the writer worked on and Network routing.
Keywords: Optimization Problem, Pheromone, Positive Feedback, Negative Feedback

INTRODUCTION

Optimization methods inspired by Nature have been unexpected successful in solving complex discrete optimization problems. Advances in the field of artificial intelligence as led to the development of such algorisms as the neutral networks, simulated annealing, evolutionary algorisms and Ant algorisms. The beauty of these techniques lies in the simple problem solving concepts observed from nature in and around us. Neural network is based on the homosapien brain, genetic algorithm the concept of evolution, simulated annealing on the natural behavior of metals and the Ant algorism based on awe-inspiring social insects [1]. All of these algorisms are to provide solution to complex problems in engineering logistics, robotics etc. These techniques provide fascinating and exciting results to various problems. The distributed and parallel implementation concepts are the key solving the problems of emerging technology present and future. A relatively new area is the swarm-based algorithm, which led to the emergence of the Ant algorithm based on the social behaviors of the ants. This was proposed by Dorigo[6] through his doctoral dissertation. This algorithm not only uses the powerful feature of cooperation through pheromone trail lying and trails following but also into consideration the local heuristic information. This algorithm is based on the behavior of social insect called swarm intelligence: the emergent collective intelligence of a group of cooperating agent, which provides distributeness, direct or indirect.

SOCIAL INSECTS

Social Insects – Ants, termites etc live in colonies. A worker usually does not perform all the tasks, instead excel in different sorts of tasks hence facilitating the activities to perform simultaneously. The behavior makes them the most efficient task achievers. The most impressive point to be notice, it that they achieve all this without any central control. An insect is a complex creature: it can process a lot of sensory inputs, modulate its behavior according to many stimuli, including interactions with the nest mates, and make decision on the basis of a large amount of information. Yet, the complexity of an individual insect is still not sufficient to explain the complexity of what social insect colonies can do. Perhaps the most difficult question is how to connect individual behavior with collective performance. The common problems that are encounter and solved by the social insects in colonies include finding food, building nest, effectively labour, responding to external challenges etc. all these are majority achieved by the self organizing capabilities. [1] Honey bees build series of parallel combs by forming chains that induce a local increase in temperature. With the combined forces of individuals in the chains, wax combs can be untwisted and be made parallel to one another. Each comb is organized in concentric rings of brood, pollen and honey. Food sources are exploited according to their quality and distance from the hive. When a bee finds a nectar source, she goes back to the hive and relinquishes her nectar to a hive bee. Then she can either start dancing to indicate to the other bees the location and the direction of the food source or continue to forage at the food source without recruiting nestwates or she can abandon her food source and become an uncommitted follower herself. If bees' colony is offered two identical food sources at the same distance from the nest, the bees exploit the sources symmetrically. However if one source is better than the other, the bees are able to exploit the better source or to switch to this better source even if discovered later. It has been experimentally shown that bees have a relatively high probability of dancing for good food source and abandoning a poor food source. This simple behavior rule allows the colony to select the better quality source [1]. Tropical wasps build complex nests comprised of series of horizontal combs protected by an external envelope and connected to each other by a peripheral or central entrance hole. Some species of termites build even more complex nests comprised of roughly cone-shaped outer walls that often have conspicuous ribs containing ventilation ducts which run from the base of the mound towards its summit, brood chamber within the central hive area, which spiral cooling vents, a royal chamber, which is a tick walled protective bunker with a few minute holes in its walls through which workers can pass, fungus gardens, draped around the hive and consisting of special galleries constructed both and abode and bellow ground which connect the mound to its forage sites. (1) Ants which are almost build animals manage to establish the shortest route paths from their colony to feeding source and back by depositing a chemical substance called pheromone on the path they moved on. The number of examples that can be quoted goes on in the study of the behavioral aspect of the social insects. All the interesting achievements of the social insects are not because of their sophisticated technological developments, but being achieved by their co-operative behavior. These insects exhibit poor individual capabilities but as a group they provide solution to complex problems.

SELF ORGANISATION IN SOCIAL INSECTS

Self Organization in a set of dynamical mechanisms where structures appear at the global level of a system from interactions among its lower level components.

Self Organization relies on

a. Positive feedback: These are the simple behavioral "rule of thumb" that promotes the creation of structures.
Example: Recruitment and reinforcement which is achieved by different mechanism in different species, such as – dancing of the bees, Pheromone trails in ants etc...

b. Negative feedback: Stabilizes the collective pattern by counterbalancing positive feedback
Example: Updating the pheromone to avoid saturation, exhaustion, crowding or competition.

c. Randomness: This enables that discovery of new solutions and can act as seeds from which nucleate and grow (i.e. provides new solutions).
Example: Foragers may get lost in an ant colony and these food sources.

d. Multiple interactions: Individuals should be able to make use of the results of their own activities as well as of others activities. This sort of group work and collective intelligence by some means of communication providing solutions to the complex problems.

Ants are well known for their capability to find the shortest paths in searching for their food. They communicate the information between the individuals regarding the paths by a chemical substance they lay called as the pheromone trails. A moving ant lays some pheromones: varying in quantity, on the ground, thus marking the path it followed by a trail of pheromones. While an isolated ant which moves randomly, encounter a previously laid trail, has high probably to follow the trail and thus reinforcing the trail with its own pheromones. The collective behavior that emerges in this form is a form of autocatalytic behavior more ants followed. This can be stead as the positive feedback, as the probability with which an ant chooses a path increased with the number of ants that choose the same path in the proceeding steps. The following is an example of how ants lead to the identification of the shortest path around an obstacle. There is a path along which the ants move by laying the pheromone trial; it could be from N (nest) to the F (food) which is shown in the Fig 3.1a. if suddenly an obstacle is placed, the previous path is cut off. The ants moving from nest to food and the ants returning back from the food to nest have to decide whether to turn to right or left (fig. 3. 1b). The decision of which way it should move depends on the intensity of the pheromone trail left by the preceding ants. The path, which has the higher pheromone trails, is most probable to be chosen. As the obstacle appeared suddenly in the path they are moving on, the first ant reaching the point of the obstacle has the same probably to turn right or left (as there

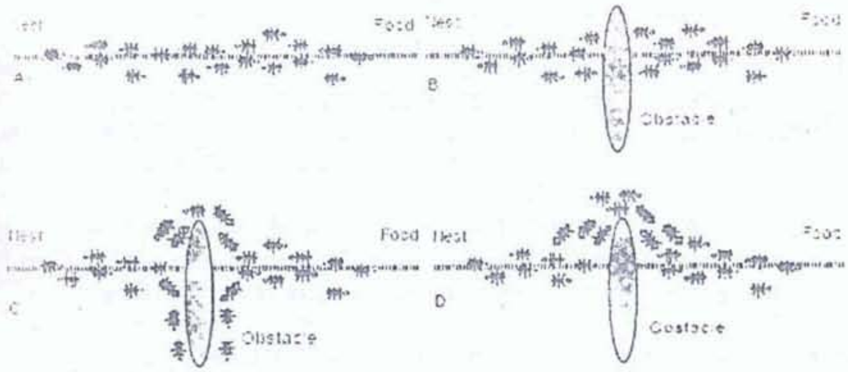


Fig. 3.1 Ants identification of the shortest path around an obstacle.

was no previous pheromone on the alternative paths.) The path to the left being shorter than the ants moving on the later path. The ants return from food to the Nest when they reach the obstacle the pheromone intensity appears only on the right path and not on the left. This makes the ants to take the shorter path and thus reinforcing the better path. Further ants passing through this point therefore prefer the shorter path and not on the longer one. This makes the ants to take the shorter path and thus reinforcing the better path. As a consequence of this the quality of pheromone on the shorter path grows faster than on the longer one and therefore the probability with any single ant choosing the path to follow is based on the shorter one. The final result of the optimum path is very quickly achieved by all the ants choosing the shorter path (fig. 3 1c).

ANTS COLONY OPTIMIZATION (ACO)

Ant Colony Optimization approach was first initiated by Dorigo in collaboration with Colorni and Mainezzo[3],and has turned out to be more than just a fun metaphor, although the initial results, obtained with an algorithm called Ants System were little disappointing, recent developments which combined the ants colony approach with local searches and other optimization methods are promising. (1)

OPTIMIZATION FOR OPTIMIZATION PROBLEMS

Ant Algorithm for Optimization Problems

A colony of artificial ants cooperates to find good solution, which are an emergent property of the ants' cooperative interaction. Based on their similarities with ant colonies in nature ant algorithms are adaptive and robust and can be applied to different versions of the same problem as well as to different optimization problems.

The main traits of artificial ants are taken from their natural model, such main traits are:

1) Artificial ants exist in colonies of cooperating individuals.

ii) They communicate indirectly by depositing (artificial) pheromone (stimergic communication).

iii. They use a sequence of local moves to find the shortest path from a starting point to a destination point (i.e. the optimal solution to a given problem)

iv) They apply a stochastic decision policy using local information only (i.e they do not look ahead) to find such best solution. If necessary in order to solve a particular optimization problem artificial ants have been enriched with some additional capabilities not present in their natural counterparts [3]. In ant systems (ant algorithms) an ant colony of a finite size searches collectively for a good solution or at least part of a solution to the optimization problem but only together they find the optimal solution. Since the optimal solution can only be found through the global cooperation of all the ants of a colony, It is an emergent result of such cooperation. In searching for a solution the ants do not communicate directly but indirectly by adding pheromone to the environment. Based on the specific problem, an ant is given a stating state and moves through a sequence of neighboring states try to find the shortest path. It moves based on a stochastic local search local search policy directly by its internal state (private information, the pheromone trials and local information encoded in the environment, public information). Such private and public information is also used by an ant to decide when to deposit pheromone. In most applications the amount of pheromone deposited is proportional to the quality of a move an ant has made. Thus the more pheromone the better the solution found. After an ant has found a solution it dies i.e. it is deleted from the system.

Applications of such ant algorithms can be divided into two classes: ant algorithms for static, and dynamic combinatorial optimization problems. In static problems the key points of the problems are defined at the beginning and do not change function of itself, thus the algorithms used to sovle such problems must be able to adapt "online" to the changes.

STATIC COMBINATORIAL OPTIMIZATION PROBLEM

Examples of applications to static combinatorial optimization problems are:
i) Traveling Salesman Problem: Where a salesman must find the shortest route by which to visit a given number of cities, each city only once.
ii) Quadratic Assignment Problem: The problem of assigning n facilities to n locations so that the cost of the assignment is minimized.
iii) Job-shop Schedule Problem: Where given a set of machines and a set of job operations must be assigned to time intervals in such a way that no maximum of all operation is minimized
iv) Vehicle Routing Problem: The object is to find minimum cost vehicle routes such that (a) very customers is visited only once and by one vehicle. (b) for every vehicle the total demand does not exceed the vehicle capacity (c) the total tour length of each vehicle does not exceed a given limit, and (d) every vehicle starts and each its tour at the same position (the depot)
v) Shortest common super sequence problem: Where given a set of strings over an alphabet – a string of minimal length that is super sequence of each string of the given set to be found (a super sequence S of string A can be obtained from A by inserting zero or more characters in A).
vi) Graph-Coloring problem: Which is the problem of finding a coloring of a graph so that the number of colours used is minimal?
vii) Sequential Ordering Problem: This consists of finding a minimum weight Hamiltonian path 2 on a directed graph with weights on the arcs and on the nodes, subject to precedent constraints among the nodes.

DYNAMIC COMBINATION OPTIMIZATION PROBLEMS

The main focus of application to the dynamic combinatorial optimization problems is on communication networks in particular on routing problems. Routing a network answers the question how to direct data traffic (e.g. phone calls) through a network i.e. which node to choose next by a data packet entering the network. Routing mainly consists of building, using and updating routing tables.

Implementations for communication networks can be divided in two classes

(a) Connection-Oriented Network Routing: where all packets of the same session follow the same path selected by a preliminary setup phase.
(b) Connectionless Network Routing: where data packets of the same session can follow different paths (internet-type networks)

ANT ALGORITHM USED IN TRAVELING SALESMAN PROBLEM.

The principle requirement of the TSP is tot find the minimal length connecting 'n' cities, each city must be visited once and only once. Let the distance between cities 'I' and 'j' be d_{ij}
d_{ij} can be calculated by the formula $d_{ij}=([x_i-x_j]^2 + [y_i-x_j]^2)^{1/2}$ Where x_i and y_i are the coordinates of the cities 'i', the paths connecting the cities are referred to as the edges by Dorigo. The following is the algorithm that is applied to the TSP

Step 1: Installation
- Give every edges (I, j) a initial value (trial)
- Place n ants at every node in the graph
- For every ant put the first node number in the tabu list
- Define the number of cycles

Step 2: Repeated until the tabulist is full:
For every ant 'k' not yet moved in
- Choose next node j (based on probability function)
- Move ant 'k' to next node 'j'
- Put node j in the tabu list ant k
- Compute ΔT_{iij}

For every edge (I,j) compute new trial intensity.

Steps 3: Memorize the shortest route
If (number of cycle < total no of cycles) or not all ants take the same tour
Then
Empty tabu list
For every ant put the present number in the tabu list
Goto 2
Else
Say shortest route

At the beginning of each tour ants are either placed randomly on the nodes or one ant is placed on each city. Dorigo [5] suggested using as many as that of the cities. The edges connecting different nodes are laid with small and equal amount of initial pheromone trail. This equal amount facilitates an unbiased problem-solving atmosphere. For each ant define a tabu list (memory) and out the first city in the tabu list to indicate it to be 'visited'. This grows within a tour and emptied between the tours. For the convergence of the solution define the number of cycles of iteration up to which it should be run. The second phase of the algorithm deals with finding the shortest paths and reinforcement of the better ones. Move each ant to the next node deciding based on the probability rule and checking the tabu list to make sure that it has not yet visited. Put the next node in the tabu list of the and to mark it as visited and ensuring it visits only once. Te transition rule helps the ant to decide on which node to move next, which in turn depends on 'visibility' and 'trail intensity'.

$$P^k_{ij}(t) = \frac{[T_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum l \varepsilon J_i^k [T_{il}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}$$

$P^k_{ij}(t)$ – Transition rule for the Ant 'K"
T_{ij} –Trail intensity.
η_{ij} –visibility.
α,β -Adjustable parameters.

The ant algorithm uses the local heuristic information by using the concept of visibility to provide better solutions. Visibility is the inverse of distance d_{ij}

$$\eta_{ij} = 1/ d_{ij}$$

That means the higher the distance between the cities lesser is the visibility.

Trail intensity is another concept where the ant explores the new solution based on the amount of the pheromone laid on the edge by the previous ants. Pheromone trail is updated on-line and is intended to represent the learned desirability, which plays an important role in choosing city j when in city i. as opposed to visibility this is global information. The change in the pheromone trial during reflects the experience gained by the ants during the problems solving.[7].

The new trial intensity can be calculated by:

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

$T_{ij}(t)$ – Total trail intensity of the edge connecting city i and j.
Where 'ρ' is the Coefficient of decay. This ranges between $0 <= \rho <= 1$.
'$1-\rho$' is the factor which determine the trial intensity after evaporation.
$(1-\rho)\, T_{ij}(t)$ is the amount of pheromone left after evaporation on the edge connecting city i and j.
Therefore 'ρ' in turn allows to forget the bad solutions.

The new trail intensity takes into account the pheromone evaporation in order to ensure sufficient solution space exploration. To do edge connecting the cities i and j is the summation of the pheromone intensity on that edge (after evaporation) and the freshly laid trail.

The freshly laid pheromone trail by the ant 'k' connecting the cities i and j is given by

$$\Delta T_{ij}^k(t) = \begin{cases} Q/L^k(t) & \text{if } j \notin T^k(t) \\ 0 & \text{if } j \in T^k(t) \end{cases}$$

The total freshly laid pheromone trail by all the ants between the city i and j is

$$\Delta T_{ij}(t) = \sum_{k=1}^{m} \Delta T^{k}_{ij}(t)$$

Q is the parameter that should be set to a value of the same order of magnitude as that of the optimal tour length.
$T^k(t)$ – is the tabu list of ant 'k'.
α,β are the adjustable parameters effecting transition rule as these govern the trail intensity and visibility. With $\alpha = 0$ in the transition rule, visibility is the only term remaining, with other terms equal to 1 which indicates that only closest cities are more likely to be selected. In such a case it ends up in local minima, which correspond to a classical stochastic algorithm. With $\beta = 0$ in transition rule, only trial intensity comes into picture indicating that only pheromone amplification is at work. This results in a rapid selection of the tours, which are not optimal. From the above computation the shortest path is memorized. The algorithm is checked if 'number of cycles' runs are less than the previously defined or if not all the ants following the same tour. If 'yes' the tabu list is released and each ants tabu list is marked with the current node and rerun to obtain the number of cycles previously defined then the obtained result is the shortest route. The above setup was run and the results obtained are encouraging for less number of cities of about 7.5. But for a higher order problem with number of cities above 3000 the results obtained were disappointing. Therefore as an effort to improve the performance of AS (Ant System), elitist ants are introduced. An elitist ant is one which reinforces the best tour found from the beginning of the trial T^+ by a quality Q/L^+ where L^+ is the length of the tour T^+. Every iteration 'e' elitist ants are added so that the best tour T^+ is reinforced by e. Q/L^+. The idea behind this is: the reinforced pheromone trail T^+ will direct the search of all the other ants towards a solution composed of some edge of the best tour. A small number of elitist ants have shown a better performance.

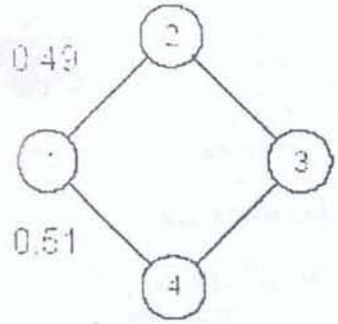
The trial intensity with the elitist approach:
$T_{ij}(t) = (1-\rho)T_{ij}(t) + \Delta T_{ij}(t) + e.\ \Delta T_{ij}^{e}(t)$
The following are the results of performance of the System compared with Tabu search and simulated annealing for 75 cities TSP problem. [7]

	BEST TOUR	AVERAGE	STD DEVIATION
AS-TSP	420	420.4	1.3
TS	420	420.6	1.5
SA	422	459.8	25.1

Comparison of the average best solution generated by Ant System (AS –TSP) tabu search (TS) and simulated annealing (SA). [7]

This results obtained from this algorithm are better than many other algorithms because of using the co-operative behaviour which is the trial intensity and also the local heuristic information which is the visibility.

Ant Algorithm used in Connecting – Oriented Network Routing
the remarkable properties of ants have encouraged researchers at Hewlett-Packard and British Telecom [4] to try and apply these concepts to the problem of load balancing and message routing in telecommunications networks. Their network is populated by agents (artificial ants) that make use of the trial-laying principles, i.e. they deposit pheromone on each node they pass during their trip through the network. The routing of calls is then decided based on the distribution of pheromone. Load balancing is essentially the construction of phone-call routing schemes that distribute the changing load over the system and minimize lost calls. Lost calls are those that never reach their destination (the caller gets only a beep signal). The basic idea is that Electronic ants are continuously generated at any node in the network and are assigned random destination nodes. On their way to the respective destination node ants move around in the network and leave their (electric) "pheromone trials". They do this by updating the so-called pheromone tables in the routers (routing tables). Every node has a pheromones table for every possible destination in the network and the destinations' neighbor nodes. Thus a node with k neighbors in a network with n node, has a pheromone table with (n-1) rows, where each row corresponds to a destination node, and has k entries. The pheromone table contains probabilities (representing the strength of pheromone), which get regularly updated as soon as an ant reaches a node (figure 4.1). updating the probabilities thus represents pheromone laying.



dest node / next node	2	4
2	0.95	0.05
3	0.49	0.51
4	0.05	0.95

4.1: A simple network configuration and the corresponding pheromone table for node 1. Ants traveling from node 1 to node 3 have a 0.49 probability to choose node 2 and a 0.51 probability to chose node 4 as their next node.

As ants at every step have good recent information about their trip from the source node to their current node, the entries in the pheromone table (table 4.1) are updated referring to the source node. Thus ants directly influence those ants traveling in the same direction. The probabilities p in the pheromone table are updated according to the following equations (4.1 and 4.2).
The entry corresponding to the node from which the ant just came is
Increase by $P_{new} = P_{old} + \Delta P / 1 + \Delta P$
And other entries decreased by
$$P_{new} = P_{old} / 1 + \Delta P$$
Where ΔP is the probability change given by the age of the ants (Note that the influence of a given ΔP is much greater on small, than on large probabilities (P_{old}). Thus the entries of rarely used nodes, those nodes with small probabilies, increase faster if traversed by ants. In order to distinguish the length of the different routes taken, ants get older with every time step while moving along the network or getting delayed at congested nodes. The older an ant gets the smaller the amount of pheromone it is able to lay and thus the influence it has on updating the pheromone tables. The value ΔP used to change the entries in the pheromone table is reduced in accordance with the age of an ant. Ants knowing their source and destination node choose their path according to the probabilities stated in the pheromone tables. The pheromone tables are then used to route an incoming phone call. The route of an incoming call is decided according by looking at the probabilities will be the next node on its way to its destination node. Calls influence the loads on the nodes and thus delay, and hereby influence the age of the ants visiting the same node. Thus there is a complex interaction between the electronic ants and the calls that are routed over the network. The pheromone mechanism of the natural ants had to be change so that there are different pheromones in the routing tables for each destination node. When we try to realize ideas from nature for technology, it is normal that nature's solutions cannot be applied directly, but need to be appropriately modified. The ant-based control method was compared to other methods (shortest path routing, and a software agent based method). Although there are some tradeoffs, ant-based control scores well in these comparisons. One problem wit ant-based control is that whenever there is a significant change in the network, it takes some time before the ant 'discover' and mark the new routes with pheromones.

CONCLUSION AND FURTHER RESEARCH

In concluding it can be observed that the Ant Algorithm as a lot of potential in solving optimization problems and research is going on in trying to improve the result of the problem solved with it and also to use ti on other problems as well as combine it with other methods like GA, SA and Neutral Network.

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