Ant Colony Optimization – A Prologue

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ABSTRACT
Swarm intelligence has been successfully applied in various domains. One of the most popular techniques of swarm intelligence uses Ant Colony Optimization (ACO) algorithms to solve continuous or mixed discrete-continuous variable optimization problems. This article starts by formally deriving the evolutionary dynamics of ant colony optimization, an important swarm intelligence algorithm. Ants of the artificial colony are able to generate successively shorter feasible path by using information accumulated in the form of a pheromone trail. Ant colony optimization is already used in too many areas from graph related problems to the medical problem and study of Genomics to communication networks etc.

Keywords—Ant colony optimization, Optimization Problems, Swarm Intelligence.

I. INTRODUCTION

In recent years, many researchers are working in the field of ant colony optimization (ACO) applicable in different areas. It is a relatively novel meta-heuristic technique and has been successfully used in many applications especially problems in combinatorial optimization. ACO algorithm models the behavior of real ant colonies in establishing the shortest path between food sources and nests. Ants can communicate with one another through chemicals called pheromones in their immediate environment. The ants release pheromone on the ground while walking from their nest to food and then go back to the nest. The ants move according to the amount of pheromones, the richer the pheromone trail on a path is, the more likely it would be followed by other ants. So a shorter path has a higher amount of pheromone in probability, ants will tend to choose a shorter path. Through this mechanism, ants will eventually find the shortest path. Artificial ants imitate the behavior of real ants, but can solve much more complicated problem than real ants can.

ACO has been widely applied to solving various combinatorial optimization problems such as Traveling Salesman Problem (TSP), Job-shop Scheduling Problem (JSP), Vehicle Routing Problem (VRP), Quadratic Assignment Problem (QAP), etc. Although ACO has a powerful capacity to find out solutions to combinational optimization problems, it has the problems of stagnation and premature convergence and the convergence speed of ACO is very slow. Those problems will be more obvious when the problem size increases. Recent studies have contributed to the improvement of the ACO to some extents, but they have little obvious effect on increasing the convergence speed and obtaining the global optimal solution. In the proposed system, the main modifications introduced by ACO are the following.

II. NATURAL BEHAVIOR OF ANTS

In the natural world, ants move randomly for finding food and return to their nest while laying down pheromone trails. Other ants follow the path of pheromone rather than moving at random and reinforce the traversed path while returning to their nest after finding food successfully like shown in figure 1. Pheromone being a chemical substance evaporates after some times; thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, more the pheromones evaporate. A short path, by comparison, gets marched over more frequently, and thus the pheromone density becomes higher on shorter paths than longer ones. Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. Broadly, the following steps elaborate the working of ACO meta-heuristic

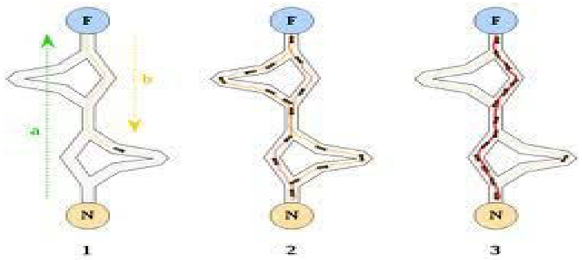

Fig: 1 Ant Colony Optimization

- Initially, ants move randomly in search of food around their colony;
- If any one of ant discovers a food source, it returns back towards the nest, leaving in its path a trail of pheromone;
- Other ants will be inclined to follow the path marked by pheromone;
- During returning to the nest, these ants strengthen the route.
- If there are multiple routes to reach the food source then, in a given amount of time, the shorter one will be traveled by more ants than the long route;
- The short route will be increasingly enhanced, and therefore become more attractive;
- The long route will eventually disappear because pheromones are volatile;
- Eventually, all the ants have determined and therefore "chosen" the shortest route.

III. LITERATURE SURVEY

Michael Brand et al. [16] applied ACO to robot path planning in a dynamic environment. They made a comparison between the two different pheromone re-initialization schemes. They also presented the computer simulation results. The proposed ACO algorithm was applied for robot path planning in a grid network. The simulation was coded in python. In the simulation, three different sizes of grid network were considered. In the proposed algorithm it was assumed that one ant can move to one of its adjacent node in four different directions, i .e left, right, up or down. Thus distance between two successive nodes was same. Firstly simulation was done for environment without obstacles. Next obstacles were added and pheromones in the network are re- initialized. Two different re-initialization plans, namely, the global initialization and the local initialization were used, tested and their performances were compared.

Denebourg et. al [17] studied natural cases of distributed activities regards ant colonies and outliner the main features of these models and so far proposed to explain ant colonies behavior. These features have been the basis for the definition of a distributed algorithm that has applied to the solution of "difficult" (NP-hard) computational problems. This type of approach was compared with other existing local path planning algorithms and results were found very encouraging.

Tatomir et al. used in their paper biologically inspired algorithms and virtual pheromones in the problem of traffic routing domain [18]. Previous approaches either focus on solving the routing problem for one individual vehicle or on the self-organization of traffic by using pheromones to stochastically guide vehicles. Their paper presents an algorithm in which ants are used to search for routes and where the traffic system piggybacks on the behavior of these ants to self-organize route guidance based on the cooperative pheromones.

Ando et al. [19] describes the way of usage of pheromone communication between vehicles to avoid traffic congestion. In their work, vehicles deposit pheromones as they travel through the traffic network. Pheromone levels increase as more vehicles pass an intersection. Pheromone also increases as vehicles slow down near the intersection. The pheromones spread via the edges of the traffic network which form pheromone hotspots. The pheromones thus dispersed in the traffic graph repel other vehicles. Through this mechanism, vehicles use pheromones solely to inform each other of congestion in an indirect manner. They do not use pheromones to guide their own route calculation algorithm, as the vehicles using the cooperative ACO approach.

The cooperative aspect of the algorithm described by Di Caro et. al resembles the ACO inspired technique in the form of AntNet routing mechanism for communication networks in their work [20]. AntNet builds and maintains routing tables over the nodes of a communication network. The forward ants move through the communication network like regular communication packets. This allows them to measure travel times on the links they traverse. After reaching their destination, the forward ants are replaced by backward ants that move in reverse direction of forward ants. These backward moving ants adjust the routing tables on all encountered nodes when they back track the path.

Gurpreet et. al [21] [22] recently has developed an algorithm for MANET environment. ANTALG is adaptable to the changing environment links of wireless networks and has proved better than many of the state of the art traditional algorithms and ant based algorithms. Various performance metrics like throughput, jitter, end to end delay, delivery ratio were considered during the time of comparison. ANTALG was based on ant colony system (ACS) algorithm which is one of the categorization of ACO meta-heuristic.

IV. ACO BACKGROUND

A. *Ant System*

Ant System was firstly introduced by M. Dorigo et. al and applied to Travelling Salesman Problem (TSP) [7, 8, and 9]. Initially, each ant is randomly allocated in each city. During the construction of a feasible solution, ants selection of the next city to be visited is done through a probabilistic decision rule. When an ant k residing at city i need to selects next city then the probability of moving to the next neighboring city j from city i is given by

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\,.\,\eta_{ij}^{\beta}}{\sum_{s\in allowed}\tau_{ij}^{\alpha}(t)\,.\,\eta_{ij}^{\beta}} & if\, j\in allowed_k\\ 0 & otherwise\end{cases} \quad (1)$$

where τ_{ij} is the intensity of trails between edge (i, j) and τ_{ij} is the heuristic visibility of edge (i, j), and $\eta_{ij}=1/d_{ij}$. α and β are two positive valued adjustable parameters to control the relative weights of the pheromone trail and of the heuristic visibility. After each ant completes its tour, the pheromone amount on each path will be adjusted with equation (2).

$$\tau_{ij}(t-1)=(1-p)\tau_{ij}(t)+\Delta\tau_{ij}(t) \quad (2)$$

$\Delta\tau_{ij}$ is calculated as:

$$\Delta\tau_{ij}(t)=\sum_{k=1}^{m}\Delta\tau_{ij}^{(k)}(t) \quad (3)$$

$$\Delta\tau_{ij}^{(k)}(t)=\begin{cases}\dfrac{Q}{L_k}, if\ ant\ k\ uses\ edge\ (i,j)\\ 0\ \ otherwise\end{cases} \quad (4)$$

$(1-r)$ is the pheromone decay parameter (0<r<1) to represent the evaporation trail. L_k is the length of the tour performed by ant k and m is the number of ants.

B. *The ACS Algorithm*

The ACS is different from the AS algorithm in the aspect of the decision rules of the ants. The global updating rules and local updating rules are both different from AS algorithm. Local updating rules are responsible for adjusting the amount of the pheromone on various paths. Main steps of ACS algorithm are

Step 1: Initiation. The amount of the pheromone on each side is initiated into a tiny constant value. Let m ants are allocated randomly to n cities.

Step 2: ACS uses the pseudorandom proportional rule in which the probability for an ant to move from city i to city j depends on a random variable q which is uniformly distributed over [0, 1], and a predefined parameter q_0.

$$J=\begin{cases}\arg\max_{ue}\ allowed_k\,(i)\left\{[\tau_{iu}]^{\alpha}.[\eta_{iu}]^{\beta}\right\} if\ \ q<q_o\\ J\ \ otherwise\end{cases} \quad (5)$$

J is a random variable determined in accordance with equation (5). This strategy obviously increases the variety of searching and avoids any premature falling into the local optimal solution.

Step 3: The local pheromone updation is performed by all the ants after the construction step is completed. Each ant applies it only to the chosen city,

$$\tau_{ij}(t+1)=(1-p)\tau_{ij}(t)+\ \ \rho\Delta\tau_0 \quad (6)$$

where 0< ρ<= 1 is a decay parameter, $\tau_0=1/n$. L_{nn} is the initial values of the pheromone trails, where n is the number of cities in the TSP and L_{nn} is the cost produced by the nearest neighbor heuristic. Equation (6) avoids selection of very strong pheromone paths formed by other ants and thus increases the explorative probability for other paths. Once the edge between city i to city j has been visited by all ants, the local updating rule makes pheromone level diminish on the edge. So, the effect of the local updating rule is to make an already edge less desirable for a following ant.

Step 4: Computation of the length of optimal path is done after m ants have travelled through all the cities.

Step 5: Global updating of pheromone. When all the ants have travelled through all the cities then updation of the amount of the pheromone on the optimal path is calculated with equations (7) and (8):

$$\tau_{ij}(t+1)=(1-p)\tau_{ij}(t)+\ \ \rho\Delta\tau_{ij}(t) \quad (6)$$

$$\Delta\tau_{ij}(t)=\begin{cases}\dfrac{1}{L_{gb}}, if\,(i,j)\in global\ \ best\ \ tour\\ 0\ \ \ \ otherwise\end{cases} \quad (7)$$

Where ρ is constant and L_{gb} is the length of global best tour.

Step 6: If the designated search number is not attained, then repeat the above steps.

V. APPLICATIONS OF ACO

Ant colony optimization algorithms have been applied to many combinatorial optimization problems, ranging from quadratic assignment to fold protein or routing vehicles and a lot of derived methods have been adapted to dynamic problems in real variables, stochastic problems, multi-targets and parallel implementations. It has also been used to produce near-optimal solutions to the travelling salesman problem. They have an advantage over simulated annealing and genetic algorithm approaches of similar problems when the graph may change dynamically; the ant colony algorithm can be run continuously and adapt to changes in real time. This is of interest in network routing and urban transportation systems.

As a very good example, ant colony optimization algorithms have been used to produce near- optimal solutions to the travelling salesman problem. The first ACO algorithm was called the Ant system [9] and it was aimed to solve the travelling salesman problem, in which the goal is to find the shortest round-trip to link a series of cities. The general algorithm is relatively simple and based on a set of ants, each making one of the possible round-trips along the cities. At each stage, the ant chooses to move from one city to another according to some rules.

The initial applications of ACO were in the domain of NP-hard combinatorial optimization problems. Concerning applications, the use of ACO for the solution of dynamic, multi-objective, stochastic, continuous and mixed-variable optimization problems is a current hot topic, as well as the creation of parallel implementations capable of taking advantage of the new available parallel hardware. Some other applications of ACO are:

- Scheduling problems.
- Vehicle routing problem.
- Assignment problem.
- Set problem.
- Travelling salesman problem.
- NP-Hard combinational problems.
- Data mining.
- Connectionless networking routing, etc.

VI. CONCLUSION

Ant colonies exhibit very interesting behavior. Even a single ant has simple and few capabilities but the behavior of a whole ant colony in collaboration is highly structured. The success of ACO lies as the result of coordinated interactions. The communication possibilities among ants are very limited; interactions must be based on very simple flows of information. In this paper we explored the implications that the study of ants' behavior can lead to solution of complex optimization problems. We introduce a distributed problem solving environment and propose its use to search for a solution to the optimization problems.

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