



ARTIFICIAL ANTS AS A TECHNIQUE OF INTELLIGENCE COMPUTATION

Mamta
M.tech Student,
R.N College of Engineering and Management

Ms. Pooja Ahlawat
Assistant Professor, Dept. of CSE
R.N College of Engineering and Management

Abstract— Ant as a single individual has a very limited effectiveness. But as a part of a well-organised colony, it becomes one powerful agent, working for the development of the colony. The ant lives for the colony and exists only as a part of it. Ant colonies are sometimes described as superorganism because it appears to operate as a unified entity. Each ant is able to communicate, learn, cooperate, and all together they are capable of develop themselves and colonise a large area. They manage such great successes by increasing the number of individuals and being exceptionally well organised. The self organising principles they are using allow a highly coordinated behaviour of the colony, furthermore bring them to accomplish complex tasks, whose difficulty far exceed the individual capabilities of a single ant.

Keywords— Ants, Intelligence Computation

I. INTRODUCTION

Ant colonies, and more generally social insect societies, are distributed systems that, in spite of the simplicity of their individuals, present a highly structured social organization. As a result of this organization, ant colonies can accomplish complex tasks that in some cases far exceed the individual capabilities of a single ant. The field of “ant algorithms” studies models derived from the observation of real ants’ behavior, and uses these models as a source of inspiration for the design of novel algorithms for the solution of optimization and distributed control problems. The main idea is that the self-organizing principles which allow the highly coordinated behavior of real ants can be exploited to coordinate populations of artificial agents that collaborate to solve computational problems. Several different aspects of the behavior of ant colonies have inspired different kinds of ant algorithms. Examples are foraging, division of labor, brood sorting, and cooperative transport. In all these examples, ants coordinate their activities via stigmergy, a form of indirect communication mediated by modifications of the environment. For example, a foraging ant deposits a chemical on the ground which increases the probability that other ants will follow the same path. Biologists have shown that many colony-level behaviors observed in social insects can be

explained via rather simple models in which only stigmergic communication is present. In other words, biologists have shown that it is often sufficient to consider stigmergic, indirect communication to explain how social insects can achieve self-organization. The idea behind ant algorithms is then to use a form of artificial stigmergy to coordinate societies of artificial agents.

One of the most successful examples of ant algorithms is known as “ant colony optimization,” or ACO, and is the subject of this book. ACO is inspired by the foraging behavior of ant colonies, and targets discrete optimization problems. This introductory chapter describes how real ants have inspired the definition of artificial ants that can solve discrete optimization problems. In many ant species, ants walking from or to a food source, deposit on the ground a substance called pheromone. Other ants are able to smell this pheromone, and its presence influences the choice of their path, that is, they tend to follow strong pheromone concentrations. The pheromone deposited on the ground forms a pheromone trail, which allows the ants to find good sources of food that have been previously identified by other ants. Using random walks and pheromones within a ground containing one nest and one food source, the ants will leave the nest, find the food and come back to the nest. After some time, the way being used by the ants will converge to the shortest path¹.

a.) Ants’ Foraging Behavior and Optimization

The visual perceptive faculty of many ant species is only rudimentarily developed and there are ant species that are completely blind. In fact, an important insight of early research on ants’ behavior was that most of the communication among individuals, or between individuals and the environment, is based on the use of chemicals produced by the ants. These chemicals are called pheromones. This is different from, for example, what happens in humans and in other higher species, whose most important senses are visual or acoustic. Particularly important for the social life of some ant species is the trail pheromone. Trail pheromone is a specific type of pheromone that some ant species, such as *Lasius niger* or the Argentine ant *Iridomyrmex humilis* (Goss, Aron, Deneubourg, & Pasteels, 1989), use for marking paths on the ground, for example, paths from food sources to the nest. By sensing pheromone trails foragers can follow the path



to food discovered by other ants. This collective trail-laying and trail-following behavior whereby an ant is influenced by a chemical trail left by other ants is the inspiring source of ACO. This chapter presents an overview of ant colony optimization (ACO) {a metaheuristic inspired by the behavior of real ants. ACO was proposed by Dorigo and colleagues [18, 14, and 19] as a method for solving hard combinatorial optimization problems. ACO algorithms may be considered to be part of swarm intelligence, that is, the research field that studies algorithms inspired by the observation of the behavior of swarms. Swarm intelligence algorithms are made up of simple individuals that cooperate through self-organization, that is, without any form of central control over the swarm members. A detailed overview of the self-organization principles exploited by these algorithms, as well as examples from biology, can be found in [8]. Many swarm intelligence algorithms have been proposed in the literature. For an overview of the field of swarm intelligence, we refer the interested reader to [4].

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Pierre Paul Grassé, a French entomologist, was one of the first researchers who investigate the social behaviour of insects. He discoveredⁱⁱ that these insects are capable to react to what he called "significant stimuli," signals that activate a genetically encoded reaction. He observed that the effects of these reactions can act as new significant stimuli for both the insect that produced them and for the other insects in the colony. Grassé used the term stigmergy to describe this particular type of indirect communication in which "the workers are stimulated by the performance they have achieved".

Stigmergy is defined as a method of indirect communication in a self-organizing emergent system where its individual parts communicate with one another by modifying their local environment. Ants communicate to one another by laying down pheromones along their trails, so where ants go within and around their ant colony is a stigmergic system. Similar phenomena can be observed for some animals, such as termites, which use pheromones to build their very complex nests by following a simple decentralized rule set. Each insect scoops up a 'mudball' or similar material from its environment, invests the ball with pheromones, and deposits it on the ground. Termites are attracted to their nestmates' pheromones

and are therefore more likely to drop their own mudballs near their neighbors'. Over time this leads to the construction of pillars, arches, tunnels and chambers.

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Using random walks and pheromones within a ground containing one nest and one food source, the ants will leave the nest, find the food and come back to the nest. After some time, the way being used by the ants will converge to the shortest pathⁱⁱⁱ. Ant behaviour fascinates in many ways. How can such a small creature, with the brain the size of a pinhead, be intelligent? Human beings learn to navigate in a city by exploring new knowledge or exploiting existing knowledge. Ants can also navigate in nature to find food and bring it back to their nests. However, ants cannot perform such tasks as individuals; they must be part of ant groups. Ants and other animals, such as certain birds and fish, navigate in their environment by relying on information provided by the others. This collective behaviour leads to what is called "swarm intelligence", which was first introduced in the context of cellular robotic systems by (Beni & Wang, 1993). The behaviour of ants as a collective or a colony inspired Dorigo in 1992 to propose an algorithm simulating their behaviour in his PhD thesis. This algorithm is called the ant colony optimization algorithm (ACO), and its aim is to find an optimal solution of NP-hard (non-deterministic polynomial-time hard) problems. ACO algorithms were originally proposed for combinatorial or discrete problems; but recently, they have also been applied to solve continuous or mixed problems.

II. LITERATURE REVIEW

Gianni Di Caro December, 1997, This paper introduces AntNet, a new routing algorithm for communications networks. AntNet is an adaptive, distributed, mobile-agents-based algorithm which was inspired by recent work on the ant metaphor. AntNet has been applied to a datagram network and been compared with both static and adaptive state-of-the-art routing algorithm. The experiments have been run for various paradigm temporal and spatial traffic distributions. AntNet showed both very good performance and robustness under all the experimental conditions with respect to its competitor.

Otto Spanial Dec, 2002, In this paper author give the detailed summary of Routing Algorithms for Mobile Multi-Hop Ad Hoc Networks In this paper we present a new on-demand routing algorithm for mobile, multi-hop ad-hoc networks. The



algorithm is based on ant algorithms which are a class of swarm intelligence. Ant algorithms try to map the solution capability of ant colonies to mathematical and engineering problems. The Ant-Colony-Based Routing Algorithm (ARA) is highly adaptive, efficient and scalable. The main goal in the design of the algorithm was to reduce the overhead for routing. Furthermore, we compare the performance of ARA with other routing protocols, including DSDV, AODV, and DSR through simulation results.

Kwag Mong Sim, 2003 , In this author give the detailed explanation of Ant Colony Optimization for Routing and Load-Balancing: survey

This survey includes:

- Providing a comparison and critique of the state-of-the-art approaches for mitigating stagnation (a major problem in many ACO algorithms);
- Surveying and comparing three major research in applying ACO in routing and load-balancing;
- Discussing new directions and identifying open problems.

The approaches for mitigating stagnation discussed include: evaporation, aging, pheromone smoothing and limiting, privileged pheromone laying and pheromone-heuristic control. The survey on ACO in routing/load-balancing includes comparison and critique of ant-based control and its ramifications, AntNet and its extensions, as well as ASGA and SynthECA. Discussions on new directions include an ongoing work of the authors in applying multiple ant colony optimizations in load-balancing. Three major groups of research are analysed in this paper, giving a good idea about the routing protocols named ABC, AntNet, AGA and SynthECA

Fedric Ducatille 2004 This paper describes AntHocNet, an algorithm for routing in mobile ad hoc networks based on ideas from the Ant Colony Optimization framework. In AntHocNet a source node reactively sets up a path to a destination node at the start of each communication session. During the course of the session, the source node uses ant agents to proactively search for alternatives and improvements of the original path. This allows to adapt to changes in the network and to construct a mesh of alternative paths between source and destination. Paths are represented in the form of distance-vector routing tables called pheromone tables. An entry of a pheromone table contains the estimated goodness of going over a certain neighbor to reach a certain destination. Data are routed stochastically over the different paths of the mesh according to these goodness estimates. In an extensive set of simulation tests, we compare AntHocNet to AODV, a reactive algorithm which is an important reference in this research area. We show that AntHocNet can out-perform AODV for different evaluation criteria under a wide range of

different scenarios. AntHocNet is also shown to scale well with respect to the number of nodes.

III. OBJECTIVE

a.) Selection of the language

After deciding to code the algorithm, the first step is to decide which language to use. The algorithm is entirely based on objects which are independent one another. Therefore the choice goes straight to any Object-Oriented language, the most common ones being C++, C#, Java & Matlab.

Since the application needs a GUI, the language needs to provide an easy access to the graphical environment with a simple interface with the mouse or keyboard. Matlab is very polyvalent and really applies to these requirements. It is also multi-platform and with the applet helps, the application can be available on any stage.

b.) Object modelling

A modeling language is any artificial language that can be used to express information or knowledge or systems in a structure that is defined by a consistent set of rules. The rules are used for interpretation of the meaning of components in the structure.

In order to develop an application which really suits to the definitions, the first action is to give a complete modeling of the specifications. First the problem will be divided into classes, linked to one another and resuming the simulated world.

We can easily define 3 main forms:

- Ant. Agent which can smell the pheromones and make a move on the ground.
- Ground. Here we will call it Playground; it is the 2-dimension space which contains the ants and the pheromones.
- Pheromones. Or traces, they are the trails which partially lead the ants.

The next modelling step is to define the relationships between these objects. There are 4 main types of link, each of them basically defining the existence of a class when the other class is destroyed. UML shows the following relationships:

- Link. Basic relationship among objects.
- Association. Family of links whose multiplicity is unlimited.
- Aggregation. When a class is a collection of other classes, but where, if the container is destroyed, its content is not.
- Composition. The multiplicity has to be 0..1 or 1, and when the container is destroyed, its content is destroyed as well.



The Playground is the central class, the ants and the traces are around it. We can precise that there is no trace without playground, but there can be ant. Traces are linked to the playground in the Composition way; if the playground is destroyed the traces are destroyed as well. The ants are a collection of the playground, but they are independent from it. They remain ants if the playground is destroyed. They are linked by an Aggregation link.

Problem Statement

ACO algorithms are very good candidates for solving combinatorial problems since the artificial ants build the solution constructively by adding one component at a time. The ACO is also suitable for the problems where the environment may change dynamically, as ACO algorithms can be run continuously and adapted to changes in real time.

The following are characteristics that should be defined for a problem to be an ACO problem as presented in Dorigo and Stützle (2004) and Blum (2005):

- There exists a finite set of components such that $c = \{c_1, c_2, \dots, c_n\}$.
- There is a set of constraints Ω defined for the problem to be solved.
- The states of the problem can be described in the form of a finite-length sequence of components such that $q = \langle \dots \rangle$. Let Q denote the set of all sequences and q denote the set of feasible sequence in satisfying the constraint Ω .
- There exists a neighbourhood structure defined between the states. q_2 is a neighbour of q_1 if q_2 can be reached from q_1 in one valid transition between the last component of q_1 and the first of component of q_2 and both q_1 and q_2 belong to Q .
- There exists a set of candidate solutions such that $S \subseteq Q$ (also $S \subseteq Q$ if we don't allow the unfeasible solutions to be constructed at all).
- There is a non-empty set of optimal solutions S^* such that $S^* \subseteq S$ and $S^* \subseteq S$.

IV. CONCLUSION

This project tried to cover the state-of-the-art studies about Ant Colony Optimisation (ACO) algorithm and its application to routing protocols. It covers recent thesis reports and introduces the latest developed protocols based on ACO.

It has been a great pleasure to study these papers. At the beginning of this project I developed my own application which simulates the ACO, which gave me the best understanding of the algorithm and its issues. Thus, the applications to the routing protocols are easier to understand since the main ideas behind them have always been inspired by the ants.

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