

Building an Identification Model Using Swarm Intelligence and Its Applications

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Abstract: Swarm intelligence (SI) is the collective behaviour of decentralized, self-organized systems, natural or artificial. SI systems are typically made up of a population of simple agents interacting locally with one another and with their environment. The inspiration often comes from nature, especially biological systems. The agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should behave, local, and to a certain degree random, interactions between such agents lead to the emergence of “intelligent” global behaviour, unknown to the individual agents. Natural examples of SI include ant colonies, bird flocking, animal herding, bacterial growth, and fish schooling.

swarm consists of a collection of mobile agents each of which behaves according to simple rules. These rules take only the interaction between neighbouring agents and the local environment into account.

The application includes Camera based Interaction is based on a simple motion detection algorithm that affects the agents’ movements as well as their colouring. Materials acquisition is one of the critical challenges faced by academic libraries. The diagnosis of hepatitis, liver disorders.

Keywords: Artificial Bee Colony, Bird flocking, Particle Swarm Optimization, Swarm Intelligence, structural optimization

I. Introduction

A swarm is a large number of homogenous, simple agents interacting locally among themselves, and their environment, with no central control to allow a global interesting behaviour to emerge. Swarm-based algorithms have recently emerged as a family of nature-inspired, population-based algorithms that are capable of producing low cost, fast, and robust solutions to several complex problems [1][2]. Swarm Intelligence (SI) can therefore be defined as a relatively new branch of Artificial Intelligence that is used to model the collective behaviour of social swarms in nature, such as ant colonies, honey bees, and bird flocks. The interacting pattern differs such as direct and indirect. Direct interaction are through visual or audio contact, such as the waggle dance of honey bees. Indirect interaction occurs when one individual changes the environment and the other individuals respond to the new environment. The indirect type of interaction is referred to as stigmergy, which essentially means communication through the environment. The study of ant colonies behavior and of their self-organizing capacities is interesting for computer scientists because it provides models of distributed organization which are useful to solve difficult optimization and distributed control problems. [4] This paper discusses two of the most popular models of swarm intelligence inspired by ants’ stigmergic behaviour and birds’ flocking behaviour.

II. Types Of Swarm Intelligence Models

The term “swarm” has been applied to many systems (in biology, engineering, computation, etc.) as they have some of the qualities that the English-language term “swarm” denotes. With the growth of the various area of “swarm” research, the “swarm” terminology has become somewhat confusing. [5] Swarm Intelligence algorithms in several optimization tasks and research problems. Swarm Intelligence principles have been successfully applied in a variety of problem domains including function optimization problems, finding optimal routes, scheduling, structural optimization, and image and data analysis. Computational modeling of swarms has been further applied to a wide-range of diverse domains, including machine learning , bioinformatics and medical informatics , dynamical systems and operations research ; they have been even applied in finance and business [6].

2.1 Swarm Intelligence Model:

Swarm intelligence models are referred to as computational models inspired by natural swarm systems. To date, several swarm intelligence models based on different natural swarm systems have been proposed in the

literature, and successfully applied in many real-life applications. Examples of swarm intelligence models are: Ant Colony Optimization , Particle Swarm Optimization [7] Artificial Bee Colony [8], Bacterial Foraging , Cat Swarm Optimization , Artificial Immune System , and Glowworm Swarm Optimization . In this paper, we will primarily focus on two of the most popular swarm intelligences models, namely, Ant Colony Optimization and Particle Swarm Optimization.

2.1.1 Particle Swarm Optimization

The particle swarm is a population-based stochastic algorithm for optimization which is based on social-psychological principles. Unlike evolutionary algorithms, the particle swarm does not use selection; typically, all population members survive from the beginning of a trial until the end. Their interactions result in iterative improvement of the quality of problem solutions over time [9].

2.1.2 Artificial Bee Colony

The classical example of a swarm is bees swarming around their hive; nevertheless the metaphor can easily be extended to other systems with a similar architecture. An ant colony can be thought of as a swarm whose individual agents are ants. Similarly a flock of birds is a swarm of birds. An immune system is a swarm of cells and molecules as well as a crowd is a swarm of people [10].

III. Models and algorithm used on the concept of swarm

3.1 Ant Colony Optimization (ACO) Model:

The first example of a successful swarm intelligence model is Ant Colony Optimization (ACO), which was introduced by M. Dorigo et al. [6], and has been originally used to solve discrete optimization problems in the late 1980s. ACO draws inspiration from the social behavior of ant colonies. It is a natural observation that a group of 'almost blind' ants can jointly figure out the shortest route between their food and their nest without any visual information. The following section presents some details about ants in nature, and shows how these relatively unsophisticated insects can cooperatively interact together to perform complex tasks necessary for their survival.

3.2 Ants Stigmergic behavior

Ants, like many other social insects, communicate with each other using volatile chemical substances known as pheromones, whose direction and intensity can be perceived with their long, mobile antennae [11]. The term "pheromone" was first introduced by P. Karlson and M. Lüscher in 1959, based on the Greek word *pherein* (means to transport) and *hormone* (means to stimulate) . There are different types of pheromones used by social insects. One example of pheromone types is alarm pheromone 5 that crushed ants produce as an alert to nearby ants to fight or escape dangerous predators and to protect their colony [12]. Another important type of pheromone is food trail pheromone. Unlike flies, most ants live on the ground and make use of the soil surface to leave pheromone trails, which can be followed by other ants on their way to search for food sources. Ants that happened to pick the shortest route to food will be the fastest to return to the nest, and will reinforce this shortest route by depositing food trail pheromone on their way back to the nest. This route will gradually attract other ants to follow, and as more ants follow the route, it becomes more attractive to other ants as showed. This autocatalytic or positive feedback process is an example of a self organizing behavior of ants in which the probability of an ant's choosing a route increases as the count of ants that already passed by that route increases.

3.3 Particle Swarm Optimization (PSO) Model

The second example of a successful swarm intelligence model is Particle Swarm Optimization (PSO), which was introduced by Russell Eberhart, an electrical engineer, and James Kennedy, a social psychologist, in 1995 [7]. PSO was originally used to solve non-linear continuous optimization problems, but more recently it has been used in many practical, real-life application problems. For example, PSO has been successfully applied to track dynamic systems [13], evolve weights and structure of neural networks , analyze human tremor , register 3D-to-3D biomedical image , control reactive power and voltage , even learning to play games and music composition . PSO draws inspiration from the sociological behaviour associated with bird flocking. It is a natural observation that birds can fly in large groups with no collision for extended long distances, making use of their effort to maintain an optimum distance between themselves and their neighbours. This section presents some details about birds in nature and overviews their capabilities, as well as their sociological flocking behavior.

IV. Experiment Comparison And Table

4.1 Real Ants Vs Artificial Ants:

Understanding a natural phenomenon and designing a nature-inspired algorithm are two related, yet different tasks. Understanding a natural phenomenon is constrained by observations and experiments, while designing a nature-inspired algorithm is only limited by one's imagination and available technology. Although the underlying principles of ant colony optimization metaheuristic are inspired by the social behaviour of ant colonies, some characteristics of artificial ants do not have to be identically the same as real ants[9]

Criteria	Real Ants	Artificial Ants
Pheromone Depositing Behaviour Pheromone is deposited both ways while ants are moving (i.e. on their forward and return ways). Pheromone is often deposited only on the return way after a candidate solution is constructed and evaluated. Pheromone Updating Amount The pheromone trail on a path is updated	in some ant species	with a pheromone amount that depends on the quantity and quality of the food [31]. Once an ant has constructed a path
Pheromone updating amount	The pheromone trail on a path is updated, in some ant species, with a pheromone amount that depends on the quantity and quality of the food	Once an ant has constructed a path, the pheromone trail of that path is updated on its return way with an amount that is inversely proportional to the path length stored in its memory
Memory Capabilities	Real ants have no memory capabilities.	Artificial ants store the paths they walked onto in their memory to be used in retracing the return path. They also use its length in determining the quantity of pheromone to deposit on their return way

summarizes the main differences between artificial ants and real ants. The artificial ant colony optimization metaheuristic just models the natural ant behaviour. Modeling serves as an interface between understanding nature and designing artificial systems. In other words, one starts from the observed natural phenomenon, tries to make a nature-inspired model of it, and then design an artificial system after exploring the model without constraints[9]

4.2 Ant Colony Optimization Algorithm

ACO is based on pheromone laying/pheromone following behaviour of real ants that helps find the shortest route between their nest and a food source. ACO has been used to solve many optimization problems such as sequential ordering , scheduling , assembly line balancing , probabilistic Traveling Salesman Problem (TSP), DNA sequencing , 2D-HP protein folding , and protein–ligand docking [38]. The main idea is to model the problem to be solved as a search for an optimal path in a weighted graph, called construction graph, and to use artificial ants to search for quality paths. A construction graph is a graph on which artificial ants iteratively deposit pheromone trails to help choose the graph nodes of quality paths that correspond to solution components. The behaviour of artificial ants simulates the behaviour of real ones in several ways: (i) artificial ants deposit pheromone trails on the nodes of quality paths to reinforce the most promising solution components of the construction graph, (ii) artificial ants construct solutions by moving through the construction graph and choose their path with respect to probabilities, which depend on the pheromone trails previously deposited, and (iii) artificial pheromone trails decrease sufficiently quickly at each iteration simulating the slowly-evaporative pheromone trail phenomena observed in real ants . A key point in the development of any ACO algorithm is to decide the fitness function based on which the components of a problem's construction graph will be rewarded with a high-level pheromone trail, and to determine how ants will exploit these promising components when constructing new solutions. The fitness function of ACO is often implicitly formulated as cost minimization of solution components, i.e., the goal of artificial ants is to walk on the construction graph and select the nodes that minimize the overall cost of the solution path[15]

Algorithm 1: Basic flow of ACO 1. Represent the solution space by a construction graph. 2. Set ACO parameters and initialize pheromone trails 3. Generate ant solutions from each ant's walk on the construction graph mediated by pheromone trails. 4. Update pheromone intensities. 5. Go to step 3, and repeat until convergence or termination conditions are met

4.3 Particle Swarm Optimization Model

PSO is a population-based search strategy that finds optimal solutions using a set of flying particles with velocities that are dynamically adjusted according to their historical performance, as well as their neighbours in the search space. While ACO solves problems whose search space can be represented as a

weighted construction graph, PSO solves problems whose solutions can be represented as a set of points in an n-dimensional solution space. The term —particles| refers to population members, which are fundamentally described as the swarm positions in the n-dimensional solution space [15].

PSO Algorithm: Basic flow of PSO 1) Initialize the swarm by randomly assigning each particle to an arbitrarily initial velocity and a position in each dimension of the solution space. 2) Evaluate the desired fitness function to be optimized for each particle's position. 3) For each individual particle, update its historically best position so far, P_i , if its current position is better than its historically best one. 4) Identify/Update the swarm's globally best particle that has the swarm's best fitness value, and set/reset its index as g and its position at P_g . 5) Update the velocities of all the particles using equation (7). 6) Move each particle to its new position using equation . 7) Repeat steps 2–6 until convergence or a stopping criterion is met (e.g., the maximum number of allowed iterations is reached; a sufficiently good fitness value is achieved; or the algorithm has not improved its performance for a number of consecutive iterations).

V. Conclusion

Particle swarm optimization is able to track dynamically varying parabolic functions. For the limited testing done here, the performance of particle swarm optimization compares favorably with other evolutionary algorithms at all three severities tested. The ability to track a 10-dimensional function was demonstrated, including tracking at severities of 0.1, 0.5, and 1.0. The investigation of tracking dynamic systems using particle swarm optimization. To be useful in practical applications, the ability of particle swarms to track and optimize highly nonlinear systems with multimodal error surfaces will need to be proven. These systems often change states chaotically, rather than linearly or randomly. Furthermore, the magnitudes of these system state changes can be significant with respect to the dynamic range of the variables, not limited to only one or two percent..

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