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Study of Swarm Intelligence Technology , Its Principals, Capabilities and Concepts for Algorithms..

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Abstract : it enables groups to form real-time systems online, connecting as 'human swarms' from anywhere in the world. A combination of real-time human input and A.I. algorithms, a Swarm A.I. system combines the knowledge, wisdom, opinions, and intuitions of live human participants as a unified emergent intelligence that can generate optimized predictions, decisions, insights, and judgments.

Swarm intelligence (SI) algorithms, including ant colony optimization, particle swarm optimization, bee-inspired algorithms, bacterial foraging optimization, firefly algorithms, fish swarm optimization and many more, have been proven to be good methods to address difficult optimization problems under stationary environments. Most SI algorithms have been developed to address stationary optimization problems and hence, they can converge on the (near-) optimum solution efficiently. However, many real-world problems have a dynamic environment that changes over time. For such dynamic optimization problems (DOPs), it is difficult for a conventional SI algorithm to track the changing optimum once the algorithm has converged on a solution. In the last two decades, there has been a growing interest of addressing DOPs using SI algorithms due to their adaptation capabilities.

This paper presents a broad review on SI technology and its applications .

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Key Words : Swarm, ants, bees, bacteria etc.

Swarm Intelligence

Swarm intelligence is an emerging field of biologically-inspired artificial intelligence based on the behavioral models of social insects such as ants, bees, wasps, termites etc. A Swarm is a configuration of tens of thousands of individuals that have chosen their own will to converge on a

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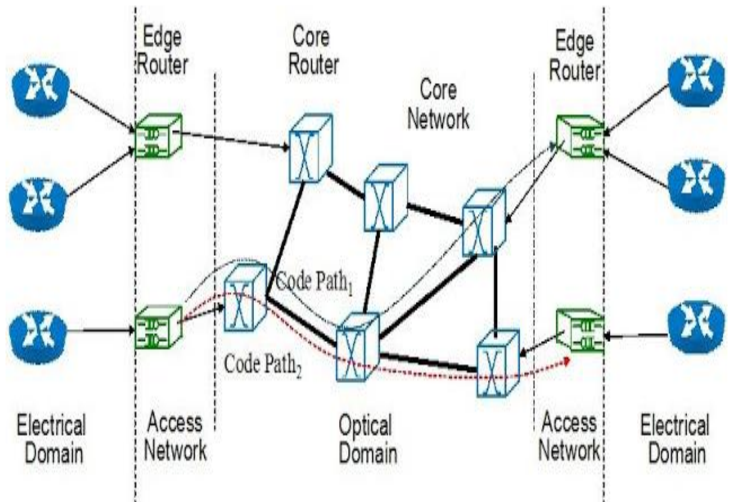
common goal. Swarm Intelligence is the Complex Collective, Self-Organized, Coordinated, Flexible and Robust Behaviour of a group following the simple rules.

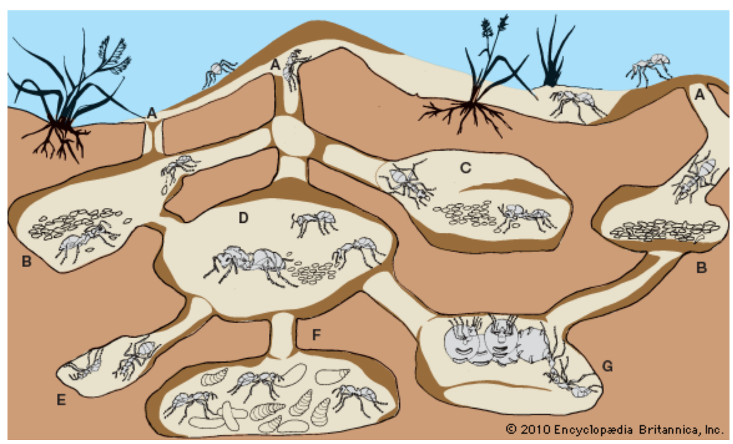


principles in swarm intelligence

1) Proximity principle: The basic units of a swarm should be capable of giving the respond back to to environmental variance triggered by interactions among agents. However, some fundamental behaviors are shared such as living-resource searching and nest-building.

2) Quality principle: A swarm should be able to respond to quality factors such as determining the safety of a location.

3) Principle of diverse response: Resources should not be concentrated in a narrow region. The distribution should be designed so that each agent will be maximally protected facing environmental fluctuations.



4) Principle of stability: The population should not change its mode of behavior every time the environment changes.

5) Principle of adaptability: The swarm is sensitive to the changes in the environment that result in different swarm behaviour.

Swarm Intelligence Capabilities:

1) Scheduling / Load Balancing: The emphasis is on the relative position of the job rather than its direct predecessor or its direct successor in the schedule and summation evaluation rule / global pheromone evaluation rule is followed.

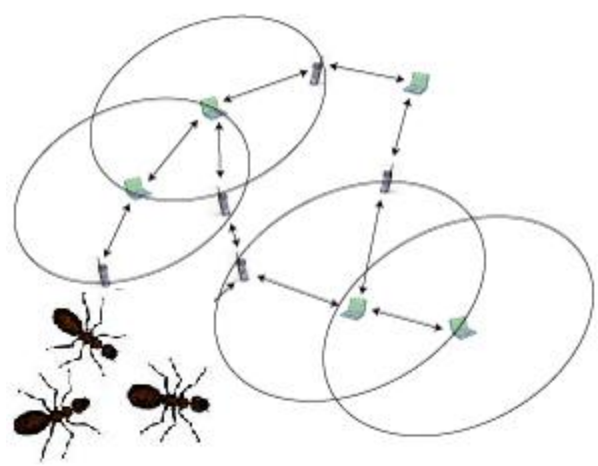
2) Clustering: A cluster is a collection of agents which are similar and are dissimilar to the agents in other clusters.

3) Optimization: An optimization problem is the problem of finding the Best Solution / Minimal Cost Solution from all the feasible solutions.

4) Routing: This is based on the principle that backward ants utilize the useful information gathered by the forward ants on their trip from source to destination.

Concepts for Swarm Intelligence Algorithms

When we consider the impact of swarm intelligence so far on computer science, two families of algorithms clearly stand out in terms of the amount of work published, degree of current activity, and the overall impact on industry. One such family is inspired directly by the pheromone-trail following behaviour of ant species, and this field is known as Ant Colony Optimization (ACO). The other such family is inspired by flocking and swarming behaviour, and the main exemplar algorithm family is known as Particle Swarm Optimization (PSO).



Also in this family are algorithms based on bacterial foraging, and some of the algorithms that are based on bee foraging; these share with PSO the broad way in which the natural phenomenon is mapped onto the concept of search within a landscape. In this section we discuss these two main families in turn.

1 Ant Colony Optimization

2 Particle Swarm Optimization and Foraging

1 Ant Colony Optimization Ant Colony Optimization (ACO) was introduced in 1996 via an algorithm called `Ant System' (AS) (Dorigo et al, 1996). The basic approach used in AS remains highly characteristic of most ACO methods in current use, and we will describe it next. Recall that, in the natural case, an ant finds a path from its nest to a food source by following the influences of pheromone trials laid down by previous ants who have previously sought food (and usually returned). AS, and ACO algorithms in general, mirror aspects of this behaviour quite faithfully. In short: an artificial ant builds a solution to the optimisation problem at hand, and lays down simple `artificial pheromone' along the route it took towards that solution. Following artificial ants then build solutions of their own, but are influenced by the pheromone trails left behind by their precursors. This is the essential idea, and starts to indicate the mapping from the natural to the artificial case. However, there are various further issues necessary to consider to make this an effective optimization algorithm.

2 Particle Swarm Optimization and Foraging

Particle swarm optimization (PSO) was established in 1995 with Kennedy and Eberhart's paper in IJCNN (Kennedy & Eberhart, 1995). The paper described a rather simple algorithm (and time has seen no need to alter its straightforward fundamentals), citing Craig Reynolds' work as inspiration (Reynolds, 1987), along with slightly later work in the modelling of bird flocks (Heppner & Grenander, 1990). The basic idea is to unite the following two notions: (i) the behaviour of a flock of birds moving in 3D space towards some goal; (ii) a swarm of solutions to an optimisation problem, moving through the multidimensional search space towards good solutions. Thus, we equate a `particle' with a candidate solution to an optimization problem. Such a particle has both a position and a velocity. Its position is, in fact, precisely the candidate solution it currently represents. Its velocity is a displacement vector in the search space, which (it hopes) will contribute towards a fruitful change in its position at the next iteration. The heart of the classic PSO algorithm is in the step which calculates a new position for the particle based on three influences. The inspiration from Reynolds (1987) is clear, but the details are quite different, and, of course, exploit the fact that the particle is moving in a search space and can measure the `fitness' of any position. The influences - the components that lead to the updated position – are:

- **Current velocity:** the particle's current velocity (obviously);
- **Personal Best:** the particle remembers the fittest position it has yet encountered, called the personal best. A component of its updated velocity is the direction from its current position to the personal best;
- **Global Best:** every particle in the swarm is aware of the best position that any particle has yet discovered (i.e. the best of the personal bests). The final component of velocity update, shared by all particles, is a vector in the direction from its current position to this globally best known position.

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