STOCHASTIC DIFFUSION: USING RECRUITMENT FOR SEARCH

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ABSTRACT

Stochastic Diffusion Search (SDS) is an efficient generic search method, originally developed as a population-based solution to the problem of best-fit pattern matching. In recent years, similarities between previously unrelated search methods have been discovered [28] and further unification and hybridisation is expected. In this context this paper seeks to establish links between SDS and Ant Algorithms, (AA). Contrary to the stigmergetic communication used in most AA, SDS uses a one-to-one recruitment system akin to the tandem-running behaviour found in certain species of ants. With reference to SDS it is claimed that efficient global decision making can emerge from interaction and communication in a population of individuals each forming hypotheses on the basis of partial evidence.

1. INTRODUCTION

In recent years there has been growing interest in a distributed mode of computation utilising interaction between simple agents. Such systems have often been inspired by observing interactions between social insects, such as ants and bees. Many algorithms inspired by the behaviour of ants, (Ant Algorithms, AA), use the principle of communication via pheromone trails to successfully tackle hard search and optimisation problems, see Dorigo, [12], for a recent review. This indirect form of communication by modification of physical environmental states has been termed stigmergetic communication. The problem solving ability of these algorithms emerges from the positive feedback mechanism and spatial and temporal characteristics of the pheromone mass recruitment system they employ. Other AA explore mechanisms for division of labour, brood sorting and cooperative transport as observed in real ant colonies, [6].

Independently of these ant-inspired algorithms, Stochastic Diffusion Search (SDS) was proposed in 1989 as a population-based pattern-matching algorithm [3] [4]. Unlike stigmergetic communication employed in AA, which is based on modification of the physical properties of the environment, SDS uses a form of direct communication between the agents similar to the tandem calling mechanism employed by one species of ants, Leptothorax Acervorum, [17].

SDS uses a population of agents. Each agent poses a hypothesis about the possible solution and evaluates it partially. Successful agents repeatedly test their hypothesis while recruiting unsuccessful agents by direct communication. This creates a positive feedback mechanism ensuring rapid convergence of agents onto promising solutions in the space of all solutions. Regions of the solution space labelled by the presence of agent clusters can be interpreted as good candidate solutions. A global solution is thus constructed from the interaction of many simple, locally operating agents forming the largest cluster. Such a cluster is dynamic in nature, yet stable, analogous to, "a forest whose contours do not change but whose individual trees do", [1].

Section 2 discusses recruitment strategies in ants and bees. In Section 3, an in-depth account of SDS applied to a novel best-fit search problem is given, together with an overview of work on SDS. Section 4 describes the relationship between SDS and social insect algorithms. Section 5 concludes by proposing SDS as a population-based metaheuristic, based on partial evaluation of hypotheses and local, direct communication between agents.

2. RECRUITMENT STRATEGIES IN SOCIAL INSECTS

Ants [15] and honey bees [13] [27] have evolved an abundance of different recruitment strategies with the purpose of assembling nestmates at some point in space e.g. for foraging purposes or emigration to a new nest site. Although the stimulative effect of a recruitment signal is often mixed with the directional function of the signal, they do constitute different functions: the stimulative function is merely used to induce following behaviour in other individuals, whereas the directional function conveys the information of where exactly to go. In ants, chemical communication through the use of pheromones constitutes the primary form of recruitment. From an evolutionary viewpoint, the most primitive strategy of recruitment seems to be tandem running: a successful foraging ant will, upon its return to the nest, attract a single ant (different strategies exist - chemical, tactile or through motor display) and physically lead this ant to the food source.

In so-called group recruitment, an ant summons several ants at a time, then leads them to the target area. In more advanced recruitment strategies, successful scouts lay a pheromone trail from the food source to the nest; this trail in itself does not have a stimulative effect. For example, ants that are stimulated by a motor display in the nest can follow the trail to the food source without additional cues from the recruiter.

Finally, the most developed form of recruitment strategy is mass recruitment. Stimulation occurs indirectly: the pheromone trail from nest to food source has both a stimulative and directional effect. Worker ants encountering the trail will follow it without the need for additional stimulation. Individual ants deposit an amount of pheromones along the trail, dependent on the perceived quality or type of the food source. The outflow of foragers is dependent on the total amount of pheromone discharged. Recruitment strategies during emigration to new nest sites show a similar wide variety of physiology and behaviour.

In honeybees, both stimulation and orientation occur primarily via motor display. Bees that have successfully located a source of nectar or pollen will engage in so called waggle dances. The direction of the dance indicates the direction of the food source, whereas the velocity of the dance depends on the distance to the find. The perceived quality and accessibility of the food source influence the probabilities that a particular forager becomes a dancer, continues exploiting the food source without recruiting or abandons the food source and becomes a follower. A follower bee follows the dance of one randomly chosen dancing bee, then tries to find the food source indicated by that bees dance.

When compared to the stimulative function of recruitment strategies in ants, bees can be said to practice group recruitment: each bee directly recruits several other bees during its time on the dance floor. However, the directional function is very different. Whereas ants either have to lead the follower to the food source - which is time consuming - or leave signposts along the way; bees do neither. They have evolved a form of symbolic communication, more adapted to their specific conditions.

Different foraging and recruitment strategies induce different quantitative performances. For ants, it was demonstrated that tandem recruitment is slower than group recruitment, which in turn is slower than mass recruitment [7]. Also, the degree of accuracy - how many ants reach the food source for which they have been recruited - is dependent on the type of communication used and differs greatly from species to species [11]. Whatever the exact details of the recruitment behaviour, it leads to a dynamical balance between exploration of the environment and exploitation of the discovered food sources.

3. STOCHASTIC DIFFUSION SEARCH

3.1. The restaurant game

A group of delegates attends a long conference in an unfamiliar town. Each night they have to find somewhere to dine. There is a large choice of restaurants, each of which offers a large variety of meals. The problem the group faces is to find the best restaurant, that is the restaurant where the maximum number of delegates would enjoy dining. Even a parallel exhaustive search through the restaurant and meal combinations would take too long to accomplish. To solve the problem delegates decide to employ a Stochastic Diffusion Search.

Each delegate acts as an agent maintaining a hypothesis identifying the best restaurant in town. Each night each delegate tests his hypothesis by dining there and randomly selecting one of the meals on offer. The next morning at breakfast every delegate who did not enjoy his meal the previous night, asks one randomly selected colleague to share his dinner impressions. If the experience was good, he also adopts this restaurant as his choice. Otherwise he simply selects another restaurant at random from those listed in 'Yellow Pages'.

Using this strategy it is found that very rapidly significant number of delegates congregate around the best restaurant in town.

Abstracting from the above algorithmic process:

Initialisation phase
  whereby all agents (delegates) generate
  an initial hypothesis (restaurant)
loop
  Test phase
    Each agent evaluates evidence for its hypothesis
    (meal degustation). Agents divide into active
    (happy diners) and inactive (disgruntled diners).
  Diffusion phase
    Inactive agents adopt a new hypothesis by either
    communication with another agent (delegate) or,
    if the selected agent is also inactive, there is no
    information flow between the agents; instead the
    selecting agent must adopt a new hypothesis
    (restaurant) at random.
endloop

By iterating through test and diffusion phases agents stochastically explore the whole solution space. However, since tests succeed more often on good candidate solutions than in regions with irrelevant information, an individual agent will spend more time examining good regions, at the same time recruiting other agents, which in turn recruit even more agents. Candidate solutions are thus identified by concentrations of a substantial population of agents.

Central to the power of SDS is its ability to escape local minima. This is achieved by the probabilistic outcome of the partial hypothesis evaluation in combination with reallocation of resources (agents) via stochastic recruitment mechanisms. Partial hypothesis evaluation allows an agent to quickly form its opinion on the quality of the investigated solution without exhaustive testing (e.g. it can find the best restaurant in town without having to try all the meals available in each).

3.2. Variations on a Theme

Many variations of the above outlined algorithm are possible: agent updates can occur synchronously for the whole population or asynchronously; the choice of another agent during diffusion can be restricted to agents in a certain neighbourhood or to the whole population; the activity of agents can be binary, integer or even real values, possibly reflecting the history of the agent; during testing, agents can vary the amount of evidence needed for a positive test of a hypothesis. During diffusion, agents can have different reactions to information from other agents, e.g. active agents could choose to communicate and modify their hypothesis according to the state of the contacted agent etc. Some of these modifications have been previously documented [2] [19] [8] [10]. Each of them has a distinct effect on the convergence and steady-state behaviour of the algorithm. However, it can be said that in all cases a dynamical balance between exploration of the solution space and exploitation of discovered solutions naturally emerges.

3.3. Previous Work on SDS

SDS was introduced in [3] [4] and subsequently applied to a variety of real-world problems: locating eyes in images of human faces (Bishop et al, 1992); lip tracking in video films [14]; self-localisation of an autonomous wheelchair [2] and site selection for wireless networks [26]. Furthermore, a neural network model of SDS using Spiking Neurons has been proposed [20]; [21]. Emergent synchronisation across a large population of neurons in this network can be interpreted as a mechanism of attentional amplification [10]. The analysis of SDS includes the proven convergence to the globally optimal solution [22] and linear time complexity [23]. Recently it has been extended to the characterisation of its steady state resource allocation [24].

4. SIMILARITIES AND DIFFERENCES BETWEEN SDS AND SOCIAL INSECTS ALGORITHMS

4.1. Comparison with social insects

The recruitment process in real insects is much more complex than that used in SDS where the process of communicating a hypothesis has been completely abstracted. An agent does not have to go through a lengthy and possibly erroneous process of tandem running or waggle dancing to communicate its hypothesis parameters to another agent.

Although no ant or bee species matches exactly the recruitment behaviour of inactive or active agents in SDS, Pratt et al [25] describe the collective decision making strategy of a species of ants that use a similar tandem running recruitment strategy during nest migration. They come to the conclusion that these ants need higher individual cognitive abilities - such as the ability to compare the quality of two nest sites - to come to an optimal solution, as opposed to ants using stigmergetic forms of communication.

Nevertheless, the fundamental similarity between SDS and social insects is that global and robust decision making in both types of systems emerges quickly from the cooperation of constituent agents, each of which individually would not be able to solve the problem within the same time frame.

4.2. Comparison with Ant Algorithms

Both SDS and Ant Algorithms are population-based approaches to search and optimisation that use a form of communication reminiscent of communication in real ants. However, most AA, and especially the ones described by the Ant Colony Optimisation (ACO) Metaheuristic [12], rely on the idea of stigmergetic communication. Good solutions emerge from temporal and spatial characteristics of the recruitment strategy: short routes receive more pheromones because it takes less time to travel them. In SDS, communication is direct, one-to-one and immediate; solutions do not emerge from temporal aspects of the recruitment system, but merely from the end result of recruitment - the spatial clustering of agents.

The most distinctive feature of SDS compared to AA is its partial hypothesis evaluation. As the computational costs of full evaluation increase, the relatively lower cost of partial hypothesis evaluation significantly increases the overall algorithm efficiency.

Non-stigmergetic AA have also been proposed. It was shown in [29] that a tandem running recruitment mechanism improves the foraging efficiency of a colony of robots. Further, an optimisation algorithm based on the foraging strategy of a primitive ant species has also been proposed, [18]. This algorithm - called API - alternates between evaluation phases and nest replacement phases. During evaluation, ants explore random points in a certain area around the nest site and remember the best sites. The evaluation phases allow for recruitment between ants: an ant with a better solution can summon an ant with a poorer solution to help it explore its area. However, it was found that recruitment on this level did not significantly improve the results obtained. Nest replacement in API can also be considered as a form of recruitment: all the ants are summoned to the optimal point found so far, then start exploring anew. Although on a very different time scale, the alternation between evaluation and nest replacement in API has similarities with the test and diffusion phases in SDS.

5. CONCLUSIONS

Pratt [25] suggests that Leptothorax Alpipennis require extra cognitive abilities in order to efficiently compare different nest sites. Although it could be that these ants need higher cognitive abilities because the exact dynamics of their recruitment process do not allow convergence on the best site in a fast enough time span, experience with SDS shows that these abilities are *in principle* not required. As long as one of the two nest sites has a higher probability of inducing recruitment, ants can come to a global decision about the best site without the ability of comparing the two sites directly.

Differences in the operation of SDS and the bulk of AA has resulted in their application in different types of search and optimisation problems. In Mitchell [16], a taxonomy of search problems has been proposed:

- Pattern matching problems, in which the goal is to locate a predefined target in a larger solution space.
- Optimisation problems, in which the goal is to select a solution from a set of candidates such that a given cost function is optimised.
- Path planning problems, in which the goal is to construct a path to reach a specified target.

Whereas SDS in its present form seems mostly applicable to the first type of search problems, AA have mostly been used for solving the second type. As such, both approaches seem complementary. However, the general principles behind SDS can clearly be applied to other problem classes. These are the principles of partial evaluation of candidate solutions and direct communication of information between agents. Using these principles, SDS can be defined as a new generic search method or *metaheuristic*, applicable to other types of problems outside the pattern-matching domain, such as model fitting; robust parameter estimation; and Inductive Logic Programming. Research in these areas is ongoing.

6. REFERENCES

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