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Article · January 2007

Source: OAI

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Abstract: This work gives an overview of the broad fiel of computational swarm intelligence and its applications in swarm robotics. Computational swarm intelligence is modelled on the social behavior of animals and its principle application is as an optimization technique. Swarm robotics is a relatively new and rapidly developing fiel which draws inspiration from swarm intelligence. It is an interesting alternative to classical approaches to robotics because of some properties of problem solving present in social insects, which is fl xible, robust, decentralized and self-organized. This work highlights the possibilities for further research.

Key–Words: Swarm Robotics, Swarm Intelligence, Computational Swarm Intelligence

1 Introduction

Nature has always inspired researchers. By simple observing we can sometimes notice the patterns, the set of rules that make seemingly chaotic processes logical. How do we think and how do we memorize? Why is evolution so important for the survival of species? How do the social insects know how to follow the path to a source of food without the global knowledge? These questions are partially answered by computational intelligence (CI). Partially, because answering some questions we are usually faced with new ones to answer.

CI as a part of broader fiel of artificia intelligence (AI) comprises of the paradigms that relate to some kind of biological or naturally occurring system. These paradigms are artificia neural networks (ANNs), fuzzy systems (FS), evolutionary computing (EC) and swarm intelligence (SI). ANNs are computational models of the human brain. Important characteristic of ANNs is capability to learn from the environment and to retain information. FS approximate human reasoning using imprecise, or fuzzy, linguistic terms. They offer solutions to a disadvantage of ordinary rule-based expert systems that cannot handle new situations not already explicitly covered in their knowledge base. EC is based on Darwin's evolutionary theory principles. It refers to computer-based problem-solving systems that use computational methods of evolutionary processes (selection, reproduction, mutation) as the fundamental components of such computational systems. SI is modelled on the social behavior of insects, fis and birds. The benefit of cooperation among individuals in a swarm can be significan in situations where global knowledge of environment does not exist. Figure 1 shows the diagram of CI paradigms where the hybrid approaches exist as well. CI is generally applied to optimization problems and many problems that can be converted to optimization problems.

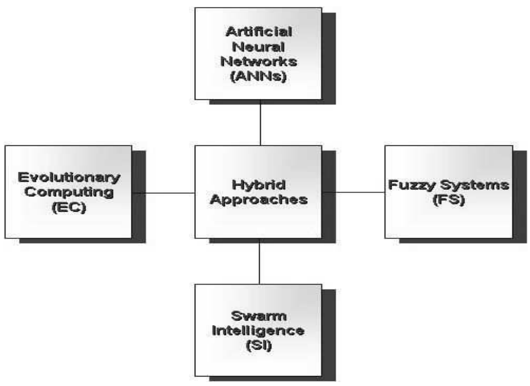

Figure 1: Computational Intelligence Paradigms.

2 Swarm Intelligence

SI systems are typically made up of a population of simple agents interacting locally with one another and with their environment. The group of individuals acting in such a manner is referred to as a swarm [1]. The term stigmergy is used to describe the indirect form of communication between individuals in a swarm via environment (one individual modifie the environment, which in return modifie the behavior of other individuals - they respond to the change). Individuals within the group interact by exchanging locally available information such that the problem (global objective) is solved more efficientl than it would be done by a single individual. Problem-solving behavior that emerges from such interactions is called swarm intelligence. Algorithmic models of that behavior are called computational swarm intelligence (CSI). For the simplicity, the name most frequently used is just ”swarm intelligence”.

Many aspects of the collective activities of social behavior in nature are self-organized. Self-organization (SO) is a set of dynamical mechanisms whereby structures appear at the global level of a system from interactions among its lower-level components [2]. SO relies on four basic ingredients:

- Positive feedback (amplification) examples are recruitment and reinforcement. For instance, recruitment to a food source is a positive feedback that relies on trail-laying and trail-following in some ant species, or dances in bees.
- Negative feedback: counterbalances positive feedback and helps to stabilize the collective pattern in the form of saturation, exhaustion or competition.
- Amplificatio of fluctuations randomness is often crucial since it enables discovery of new solutions.
- Multiple interactions: a minimal density of mutually tolerant individuals is required to generate a self-organized structure.

The objective of SI is to model the simple behavior of the individuals, their local interactions with the environment and neighboring individuals, in order to obtain more complex behaviors that can be used to solve complex problems, mostly optimization problems. A critical number of individuals are required for ”intelligence” to arise.

The two best known SI algorithms are: Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO).

2.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) [3] was originally inspired by the flockin behavior of birds. In terms of this bird flockin analogy, a particle swarm optimizer consists of a number of particles, or birds, that fl around and search space, or the sky, for the best location. The individuals communicate either directly or indirectly with one another search directions (gradients).

Each of the particles in a swarm corresponds to a simple agent that moves through a multi-dimensional search space sampling an objective function at various positions. The best solution can be represented as a point or surface in the search space. Potential solutions are plotted in this space and seeded with an initial velocity. The motion of a given particle is dictated by its velocity which is continuously updated in order to pull it towards its own best position and the best positions experienced by the neighbors in the swarm. The performance of each particle is evaluated using a predefine fitnes function which encapsulates the characteristics of the optimization problem. Over time, particles accelerate towards those with better fit ness values.

PSO is a simple, but powerful search technique. It has few parameters to adjust and is easy to implement.

2.2 Ant Colony Optimization

Artificia ant systems model the social interaction and seemingly intelligent behavior of naturally occurring colonies of ants. Observing the ant colonies we can notice that, although the behavior of a single ant doesn’t seem logical, the resulting behavior of the colony solves the problems of great importance for the survival. The ants use the trail-laying trail-following behavior to communicate via environment. They lay pheromone which attracts other ants. The emergent behavior of the colony is observed in their ability to, amongst others, locate optimal food resources and perform nest brooming, including cemetery maintenance.

The Ant Colony Optimization (ACO) [4] represents the model of the collective foraging behavior of ants. Deneubourg et al. [5] showed that path selection to a food source is based on self-organization. In the Binary Bridge experiment, two ants are taking the paths of different length from the nest to a food source. The ant that will return firs to the nest is the one taking the shorter path. This path will, therefore, contain the larger pheromone concentration and it will attract other ants to take the same route. As more and more ants start to follow the trail of higher pheromone concentration, a positive feedback loop is created until all the ants follow the shortest path. Thus, social interaction and coordination for foraging occurs indirectly through pheromone deposits which modify the environment.

The basic idea underlying all ant-based algorithms is to use a positive feedback mechanism, based on an analogy with the trail-laying trail-following behavior of some species of ants, to reinforce the good solutions. A virtual pheromone is used as reinforcement to allow the good solutions to be memorized and then potentially used to make up better solutions. Premature convergence (stagnation) of the algorithm to good, though not very good solutions, is avoided by implementing a negative feedback through pheromone evaporation and that also includes a time scale in the algorithm. The time scale must not be too large, otherwise suboptimal premature convergence behavior might occur. It must not be too short either; otherwise no cooperative behavior can emerge. Cooperative behavior is another important concept: ants in the next iteration use the pheromone trail from the ants in the previous one to guide their exploration.

Some optimization algorithms model the behavior of honeybees. The recently developed Bees algorithm of Cardiff University implements techniques that bees employ when foraging for food [6].

2.3 Swarm Intelligence Applications

SI techniques are population-based stochastic methods used in combinatorial optimization problems in which the collective behavior of relatively simple individuals arises from their local interactions with their environment to produce functional global patterns. There is no best optimization technique for all the problems. Each method has its advantages, and the set of parameters define the quality of the solution.

Engineers are increasingly interested in swarm behavior since the resulting swarm intelligence can be applied in optimization (e.g. in telecommunication systems), robotics, traffi patterns in transportation systems, military applications, etc. More and more new applications arise from the research in SI. Every problem, application, that in its base has some kind of optimization can be tackled with SI techniques.

Swarm robotics is a rapidly developing fiel that gets the inspiration from swarm intelligence. The animal societies are good examples of what future robotic swarms might achieve, but they are not at all limited by biological plausibility. The efficien y, fl xibility, robustness, and cost are possible criteria that should be used in development of such systems.

3 Swarm Robotics

Swarm robotics (SR) refers to the application of swarm intelligence techniques to the analysis of activities in which the agents are physical robotic devices that can effect changes in their environments based on intelligent decision-making from various input. The goal of this approach is to study the design of robots (both their physical body and their controlling behaviors) such that a desired collective behavior emerges from the inter-robot interactions and the interactions of the robots with the environment, inspired but not limited by the emergent behavior observed in social insects.

SI techniques as ACO and PSO can be used as a control algorithm for distributed robot swarms [7], but a good problem-solving system does not have to be biologically relevant. However, the remarkable success of social insects in surviving and colonizing our planet can serve as a starting point for new metaphors in engineering and computer science.

3.1 Criteria for Swarm Robotics

What makes a system swarm-robotic?

Autonomy – It is required that the individuals that make up the swarm-robotic system are autonomous robots. They are able to physically interact with the environment and affect it.

Large number – A large number of units is required as well, so the cooperative behavior (and swarm intelligence) may occur. The minimum number is hard to defin and justify. The swarm-robotic system can be made of few homogeneous groups of robots consisted of large number of units. Highly heterogeneous robot groups tend to fall outside swarm robotics.

Limited capabilities – The robots in a swarm should be relatively incapable or inefficien on their own with respect to the task at hand.

Scalability and robustness – A swarm-robotic system needs to be scalable and robust. Adding the new units will improve the performance of the overall system and on the other hand, loosing some units will not cause the catastrophic failure.

Distributed coordination – The robots in a swarm should only have local and limited sensing and communication abilities. The coordination between the robots is distributed. The use of a global channel for the coordination would influenc the autonomy of the units.

Though these criteria are not to be used to determine whether a system is swarm-robotic or not, they can be used to measure the degree to which the term ”swarm-robotic” might apply.

3.2 Advantages to Classical Approaches

Some advantages of swarm-robotic systems make them more appealing then classical robotics. Some tasks may be too complex for a single robot to perform. The solution speed is increased when using large number of robots, even when the cooperation is not present. It is easier to design simple robot units required for a swarm. The communication between the robots is reduced because of the indirect interactions.

SR is currently one of the most important application areas of SI. Swarms provide the possibility of enhanced task performance, high reliability (fault tolerance), low unit complexity and decreased cost over traditional robotic systems. They can accomplish some tasks that would be impossible for a single robot to achieve.

Research in the fiel of SR shows that a set of relatively primitive individual behaviors enhanced with communication will produce a large set of complex swarm behaviors.

3.3 Swarm Robotics Applications

Regarding the domain of applications, the swarm-robotic systems can be applied in various scenarios.

Foraging – This scenario has many different applications and demands several fundamental skills from a group of robots, such as collective exploration, shortest path finding and efficien task allocation [8]. It also includes the transport sub-task, which covers the important issue of *collective transport* [9]. Some examples of applications of foraging scenario are toxic waste clean-up, search and rescue (SAR) and collection of terrain samples.

Dangerous tasks – Individuals that create a swarm-robotic system are dispensable making the system suitable for domains that contain dangerous tasks. For instance, demining can be cheaply accomplished by a swarm of robots [10].

Exploration and mapping – Advancements in the design that lead to further miniaturization and lower cost of robotic units open many new possible scenarios. The inspection of all kinds of engineered structures can be carried out using swarms of robots, where process is usually time consuming and cost intensive [11]. Robots in a swarm have limited sensing capabilities, but collective perception of the swarm can be used to create global knowledge (e.g. construct a map of the area). In [12] the trophallaxis-inspired strategy was used to successfully perform collective perception. Spears et al. [13] use different types of trilateration as a localization method and combine it with the information exchange between robots to create a distributed framework for new applications. Some applications still appear to be distant future, such as use of robot swarms for Space exploration or use of nanorobots moving through human veins and arteries for medical purposes (e.g. to figh certain types of cancer).

Many active projects confir the enormous interest in the fiel of SR. The Pheromone Robotics project [14] aimed to provide a robust, scalable approach for coordinating actions of large numbers of small-scale robots to achieve large scale results in surveillance, reconnaissance, hazard detection, path finding payload conveyance, and small-scale actuation. Inspired by the chemical markers used by the insects (especially ants) for communication and coordination, the researchers exploited the notion of a ”virtual pheromone”, implemented using simple beacons and directional sensors mounted on each robot. Collections of robots are able to perform complex tasks such as leading the way through a building to a hidden intruder or locating critical choke points. This concept can be used for the urban search and rescue (USAR) operations as well, where the team of robots can be sent to the site to investigate environmental parameters, search for survivors, and locate sources of hazards such as chemical or gas spills, toxic pollution, pipe leaks, radioactivity, etc.

The objective of the Swarm-Bots project [15] was the design, hardware implementation, test and use of self-assembling, self-organizing, metamorphic robotic systems called swarm-bots, which were composed of a swarm of assembled s-bots. Inspired by the collective behavior of social insects colonies, simple robots, referred to as s-bots, were capable of autonomously carrying out individual and collective behavior by exploiting local interactions among the s-bots and between the s-bots and their environment. The swarm of s-bots can be used for a collective transport, or to reach the points hardly reachable for a single unit.

Still active FP6-IST project called I-SWARM [16] aims to take a leap forward in robotics research by combining experts in microrobotics, in distributed and adaptive systems as well as in self-organizing biological swarm systems. The swarm will consist of a huge number of heterogeneous robots, differing in the type of sensors, manipulators and computational power. Such a robot swarm is expected to perform a variety of applications, including micro assembly, biological, medical or cleaning tasks.

The Swarmanoid project is a follow-up of the Swarm-bots project [17]. The main scientifi objective of the proposed research is the design, implementation and control of a heterogeneous distributed robotic system capable of operating in a fully 3-dimensional environment.

4 Conclusions

This work has given the detailed overview of current swarm intelligence research and its applications in swarm robotics. Swarm robotics is an interesting alternative to classical approaches to robotics because of some properties of problem solving by social insects, which is fl xible, robust, decentralized and self-organized.

Advantages of swarm-based robotics are numerous. Some tasks may be too complex for a single robot to perform. The speed is increased when using several robots and it is easier to design a robot due to its simplicity. Rapid progress of hardware brings innovations in robot design allowing further minimization. The communication between robots is reduced, because of the interactions through the environment.

We are reaching a stage in technology where it is no longer possible to use traditional, centralized, hierarchical command and control techniques to deal with systems that have thousands or even millions of dynamically changing, communicating, and heterogeneous entities. The type of solution swarm robotics offers, and swarm intelligence in general, is the only way of moving forward when it comes to control of complex distributed systems.

5 Future Work

Swarm robotics brings several issues that can be addressed in the future lines of research. Lack of global knowledge can lead to a deadlock, and the group of robots cannot progress. New solutions are needed for prevention and evasion of the state of stagnation. Programming the robots represents an issue when the pathways to solutions are not predefine but emergent. If applied well, self-organization endows the swarm with the ability to adapt to unpredicted situations. Interesting directions in future research may include ways of enhancing indirect communication among robots. Being relatively new, the fiel of swarm robotics leaves a lot of room for further research.

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