Emergence of Cooperation in Swarm Systems: State of the Art

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Abstract— **This article presents a survey of prevalent results within research pertaining to emergent cooperation in swarm-based systems. Results reviewed maintain particular reference to research that uses biologically inspired design principles and concepts, such as emergence, evolution and self-organization, as a means of attaining cooperative behavior in swarm systems. The review presents an introduction to emergent cooperation in artificial life research followed by a survey of emergent cooperation in swarm-based systems that includes artificial ants, and simulated multi-robot systems that follow swarm like behaviors. The mechanisms deemed to be responsible for emergent cooperation in these systems are elucidated and their key limitations highlighted. The core of this article argues that even though emergent cooperative behavior derived within swarm systems is still in its infancy, it holds considerable future potential, as a means of problem solving in a disparate range of application domains where systems comprised of many interacting components must cooperatively solve some global task.**

Index Terms — **Emergence, cooperative behavior, self-organization, artificial evolution.**

I. INTRODUCTION

The global behavior and complexity of biological systems such as ant colonies and certain distributed artificial systems are considered to be an emergent property of the interactions between the different agents that make up the whole system. Desirable emergent behavior has been observed in many biological systems, though reproducing these conditions in artificial systems has proved to be difficult and there is potential for the emergence of undesirable behaviors. It is therefore essential to be able to understand the mechanisms that motivate emergent behaviors in these systems. To date, research that qualitatively measures and evaluates mechanisms that underlie and motivate emergent cooperative behavior in biological, artificial, and real world systems remains largely in stage of research infancy. Current mathematical and empirical tools have provided only a partial insight into elucidating mechanisms responsible for cooperation, and then only in systems of an abstract or simple nature. The concept of emergent behavior has propagated many ideas about emergent cooperative behavior in biological systems. These ideas have now been adopted by roboticists and computer scientists alike, and have gained prevalence since the rise of a globalized information society brought on by the proliferation of global decentralized systems such as the Internet.

In the mid twentieth century, Grey Walter[2] and his colleagues studied turtle-like robots equipped with light and touch sensors and very simple behaviors. When placed together, these robots exhibited complex social behavior in response to each other's movements [7]. Early research in decentralized systems [5] suggested that complexity at a group level might be attainable with very simple individual agents, with no need for central control. A derivative of this idea is biologically inspired artificial systems such as swarm systems, that are typically designed using an evolutionary computation methodology such that a desired global behavior emerges from interaction of the systems components [9]. It is argued by many researchers [31] that the use of biologically inspired principles such as evolution and emergence in the purposeful design of complex artificial systems is needed in order to replace ineffective preprogrammed and centralized design methodologies.

With relatively few exceptions, and then only in multi-robot systems containing relatively few robots [20], the majority of research in emergent cooperative behavior is restricted to simulated problem domains given the inherent complexity of applying evolutionary design principles to collective behaviors in groups of real robots [16]. This is especially true in swarm-based systems, which by definition contain thousands of individuals. Hence, this paper surveys only research pertaining to the study of emergent cooperative behavior using biologically inspired design principles within simulated problem domains. An important future direction that the survey emphasizes is the gaining of more insightful knowledge into the design of algorithms for emergent cooperation in swarm systems. If emergent cooperative behavior in swarm systems was sufficiently understood, purposeful design of cooperative behavior could be applied to benefit a variety of application domains including telecommunications [10], aerospace and space exploration [6] and multi-robot systems [21].

As a final introductory note, in the literature various researchers have adopted the use of various nomenclatures

[2] Grey Walter was a neuro-physiologist, who in the late nineteen forties carried out pioneering research on mobile autonomous robots at the Burden Neurological Institute in Bristol, England as part of his goal to model brain function.

that are ambiguous in defining the term *cooperation*. Such terminology often suffers from the frame of reference problem [27], as it is typically defined according to the perspectives and interests of the researchers conducting the study. Thus, for the purposes of this survey, we are concerned not with a definition of cooperation, but rather with research that uses biologically inspired design principles within swarm systems as a means of motivating two or more individuals to solve a predefined problem of a global nature that could not otherwise be solved by a single individual.

II. Emergent Cooperation in Swarm-based Systems

A. Introductory Note

The validity and importance of large artificial swarm systems is clear from drawing parallels to the biological complexity of swarm-based systems such as ant colonies. In such systems global behavior is considered to be an emergent property of the interactions of the many different components that make up the whole system. Desirable emergent behavior has been observed in many biological systems, though reproducing these conditions in artificial systems has proved to be difficult as there is potential for the emergence of undesirable behaviors. Certain swarm systems model biological systems that contain hundreds or thousands of agents, such as ant and termite colonies. Social insect colonies present excellent examples of how collectively intelligent systems can be generated by the interaction of a large number of relatively simple agents. Based on the social insect metaphor, *swarm intelligence* has emerged as a novel approach to the design of distributed systems, with emphasis upon flexibility, and robustness. There has been a significant concentration of research on the study of emergent behavior in simulated ant colonies [9]. Studies of swarm-based systems have been popularized by certain artificial life simulators and applications. These include *Swarm* [17], *MANTA* [15], *Tierra* [28], and *Avida* [1].

B. Biologically Inspired Artificial Ants

Drogoul *et al.* [12], [13], [14] presented a simulation model of social organization in an ant colony termed: *MANTA* (*M*odel of an *ANT*-hill *A*ctivity), which was designed to explore the contribution of emergent functionality such as division of labor and *sociogenesis*[3] [32] on emergent cooperation. Drogoul *et al.* observed the emergence of cooperative behavior beneficial to the colony, similar to social phenomena generally observed among *eusocial*[4] insects. Results elucidated that emergent division of labour improved the efficiency of emergent functionality in the population. Such emergent functionality included cooperative foraging and sorting behavior. The authors concluded that the notion of emergent cooperation remains very unclear, difficult to define, and that many of the behaviors viewed as cooperative emerged as a result of the competitive interaction that occurs between individuals in a constrained environment with limited resources.

In an extended version of MANTA [15], certain experiments were designed to investigate the evolution of a process known as *sociogeneses*, where multiple ant queens needed to cooperate in order for a new ant colony to emerge and survive. Two types of sociogenesis experiments were conducted, those using only a single queen, termed *monogynous sociogeneses*, and those using multiple queens, termed *polygynous sociogeneses*. The hypothesis for the *Sociogeneses* experiments was that emergent functionality within a population would be improved by the emergence of a parallel emergent social structure. In this case the emergent functionality was a cooperative sorting task, and the parallel emergent social structure was the division of labor. In order to facilitate the emergence of cooperation for the sorting task at the colony level, an artificial evolution algorithm was executed, where the selection and reproduction of each new generation was based on the individual genetic design of each artificial ant. In the evolutionary process specialized behavior emerged which served to removed redundant behaviors and therefore increase the probability of an ant successfully completing its task. In the *polygynous sociogeneses* experiments, either only a single queen survived, or a single queen emerged as the leader of the colony while the other queen ants became analogous to worker ants. An important trade-off in competitive versus cooperative behavior between the queens was evident from these experiments. This trade-off proved to be important for the survival of the ant colony as a whole. Cooperative behavior emerged between the queen ants during the initial stage of the colonies growth, where this behavior took the form of one of the queens taking care of the larvae while others searched for food. The authors concluded that emergent functionality at the colony level was potentially improved via the parallel emergence of a social structure such as cooperation. In these experiments, emergent cooperation was facilitated by the concurrent emergence of a division of labor social structure.

Whilst the parallels between emergent cooperative behaviors attained under experiments executed using the MANTA simulation model, and the emergent behavior observed in real ants makes them intrinsically interesting, what is lacking in this research is a qualitative analysis of the emergent behavior and the mechanisms that lead to cooperative behavior and the concurrent emergence of the division of labor social structure. Also, the artificial ants operated within a simple and constrained grid world environment, so a realistic simulation of ant behaviors was limited, and only a single case study for emergent collective behavior was presented. Thus, it remains unclear if the

[3] Socio-genesis is defined as a behavioral process observed in many species of ants, where the newly fertilized queen initiates a new society alone.

[4] The term: *eusocial* describes the most highly developed form of animal societies, such as those of colonial ants, termites, wasps, and bees. Typically there is extensive division of labour and cooperation, with various castes each performing particular tasks, such as food-gathering, defense, or tending to the young. Reproduction is by an elite group of fertile individuals, assisted by sterile workers. This definition was taken from the Dictionary of Biology, Oxford University Press © Market House Books Limited, 2000.

approach is suitable to a more generalized simulation of emergent social structures that would further test the authors' hypothesis that emergent social structures such as the division of labor facilitate emergent cooperative behavior, which in turn strengthens emergent functionality such as a sorting task.

Also in the theme of artificial ant systems, Perez-Uribe *et al.* [30] conducted experiments in the context of an artificial evolution process, in order to study the impact of genetic relatedness and different types of genetic selection in the evolution of cooperation for a foraging task. The task was composed of multiple trials where each trial consisted of two phases. In the first phase each ant activated one of three pre-specified behaviors, and in the second phase a group of twenty ants began searching for the food items in their environment. The transportation of certain large food items required that two ants cooperate in order to achieve the task. This cooperative foraging task was modeled within a mobile robot simulator, with which the authors were able to vary parameters such as the value of food, an ant's genetic specification, and the type of genetic selection and reproduction used by the evolutionary process. Changing these parameters served to place selective pressure on the evolution of cooperative behaviors. The authors argued that the group of robots modeled by the simulator maintained limitations and properties similar to real ants due to their small size, as well as stochastic and time dependent dynamics modeled upon the constraints of a yet to be implemented counter-part physical setup.

Artificial ants were rewarded differing fitness scores for either individual or cooperative transportation of food items, such that the total performance of the colony was maximized if ants cooperatively transported food items as opposed to acting individually. In the experimental setup, groups of ants tested were either homogenous or heterogeneous, where the method of genetic selection, which either reproduced the next generation from a collection of individuals from different colonies or from different colonies as a whole, delineated homogenous and heterogeneous colonies. The authors highlighted that the colony-based form of genetic selection and reproduction favored emergent cooperative behaviors, and that cooperative behavior had a low probability of emerging in heterogeneous colonies, where an individual-based form of genetic selection and reproduction was used. In particular, the resulting number of cooperative behaviors was higher in experiments using colony-based selection. The authors stated this to be a result of colony-based selection favoring individuals that cooperate and not ones that adopt specialized behaviors in the foraging of small food items for their own benefit. The experiments also suggested that genetic relatedness within an artificial ant colony assumes a role in the emergence of cooperative behavior, as homogenous colonies performed better in the cooperative foraging task domain than heterogeneous ones. The authors argued that these results maintained biological plausibility, based upon predictions made by certain biologists [18] stating that groups should be more efficient when genetic selection acts at the colony-level and when there is a high degree of relatedness within groups. Though, the same results also yielded no significant difference between homogenous colonies using colony-based selection and homogeneous colonies using individual-based selection, indicating that future research should continue to investigate the role of genetic relatedness in facilitating emergent cooperative behavior.

It is clear that modeling emergent cooperative behavior in an artificial ant system using a multi-robot simulator and evolutionary computation is fruitful, since social insects have a very long generation time and it is inherently difficult to study the evolution of complex social structures such as cooperation. Though, the results illustrated that cooperative behavior is more likely to emerge under the colony-based form of genetic selection within a homogenous colony, the authors did not clearly state the significance of these results, beyond remarking upon their biological plausibility. Whilst the inherent complexity of maintaining and analyzing the behavior of large groups of artificial ants within an artificial evolution process justifies the use of a simple form of the cooperative foraging task, only twenty ants, and a simple form of genetic based behavioral encoding, the authors did not clearly specify which mechanisms were deemed to be responsible for cooperative behavior, beyond the conclusion that performance differences were the result of genetic relatedness.

Aside from simulations that reproduce cooperative behavior in swarm-like systems, certain biological principles that define cooperative behavior in these systems have also been applied to solving classical artificial intelligence problems. For example, certain researchers have applied biological principles from cooperative behavior in real ants to solving combinatorial optimization problems such as the traveling salesman problem [15], and the quadratic assignment problem [19]. Dorigo and Gambardella [11] introduced a distributed algorithm called *Ant Colony System* that is based upon the global behavior of an ant colony and is applied to the traveling salesman problem. The Ant Colony System is comprised of many artificial ants, with simple capabilities to mimic the behavior of real ants, where these ants cooperate in order to find good solutions to the traveling salesman problem. The artificial ants use an indirect form of communication mediated by simulated pheromone trails that they deposit on the edges of the traveling salesman problem graph while cooperatively constructing solutions. The Ant Colony System was inspired by the capability of real ants to find the shortest path from a food source to their nest via the use of pheromone information [3]. The artificial ants cooperate by exchanging information via an artificial pheromone. Ants use this pheromone information as the medium to communicate information among themselves regarding path length and which path to travel. The emergent cooperative behavior as evident from the experiments run is as follows. Once all ants have traversed the graph, the best performing ant pheromone deposits its pheromone at the end of iteration t, therefore defining a preferred route for search in the next iteration of the algorithm. So, during iteration $t+1$ ants will detect edges belonging to the best traversal of the graph and will choose to traverse these edges with a higher degree of probability. Thus the cooperative behavior that emerges is a form of auto catalytic behavior where the more the ants follow a trail, the more attractive the trail becomes as a potential path for other ants. This process is characterized by a positive feedback loop, where the probability with which an ant chooses a path increases with the number of ants that previously chose the same path. Though, whenever an ant visits an edge it diminishes the amount of pheromone on that edge, therefore making these edges less desirable to other ants in the future. This allowed for the possibility of an improved future search in the neighborhood of the previous best search.

The authors highlighted the effectiveness of the Ant Colony System by comparing a cooperative with a non-cooperative search. The search executed by a given number of cooperative ants proved superior to that of a search carried out by the same number of ants, each working independently from the others. When no cooperation was used the algorithm slowly derived a sub-optimal solution, while when the ants cooperated, an optimal solution, not within a local optima, was quickly found. For this research, the emergence of cooperative behavior was limited by the constraints of the task environment, so the applicability of such emergent cooperation principles to other combinatorial optimization problems remains unclear.

C. *Swarm-bots*

Swarm-bots is a research endeavor not concerned with the modeling or simulation of real world biological systems but rather with using biologically inspired design principles in the simulation, and then physical construction of, mobile robots that exploit concepts such as emergent cooperation, self-assembly and self-organization in order to accomplish their goals. The individual robots are called s-bots, where two or more s-bots that have self-assembled in order to perform some task are called a swarm-bot [23]. The key idea of the research is that swarm-bots combine the advantages of swarm intelligence as well as the flexibility of self-reconfiguration, as they are able to self-assemble and self-organize so as to solve problems that could not otherwise be solved by a single s-bot.

As part of the swarm-bots initiative, Nolfi *et al.* [25] conducted several experiments to address the problem of how a group of s-bots could coordinate their movements and actions so as to cooperatively move objects in the environment as far as possible within a given period of time. This research differs from other experiments in the swarm-bots endeavor in that in this case the s-bots are given a task for which they must cooperate in order to solve. Other swarm-bot research [29] simply maintained the goal of achieving some form of aggregated behavior, which the authors stated would be a prerequisite for various forms of cooperative behavior. Nolfi *et al.* [25] conducted a set of experiments designed to facilitate emergent cooperative behavior, where a group of eight s-bots were connected to an object, or connected so as to form a closed structure around an object, and were given the task of moving the object as far as possible in the least amount of time. In the first set of experiments the eight s-bots used what the authors termed the *ant formation*, which connected all s-bots to the object, but there were no links between the s-bots themselves. The result was dependent upon the weight of the object, such that the s-bots cooperatively negotiated to either push or pull the object to their destination. In the second set of experiments, s-bots were assembled so as to form a circular structure around the object. The results were similar to those obtained with the ant-formation, with the exception that the s-bot formation deformed its shape so that some s-bots pushed the object, while other s-bots pulled the object. The mechanism deemed to be primarily responsible for these results was the neural controllers of individual s-bots, which evolved the capability to cooperatively coordinate movement when connected to either each other or the object. That is, each s-bot was inclined to follow the direction that the majority of s-bots followed at a given time.

Despite the interesting nature of these results, their contribution to the swarm-bots research initiative, and a clearly defined task for the evaluation of emergent behavior, the research lacks formalized methods for the analysis of emergent cooperative behavior that led to the successful transport of objects, meaning that emergent cooperative behavior was only examined from an observational perspective. Also, given that the s-bots are connected to each other or the object at the start of the experiment, the s-bots are forced to cooperate in order to satisfy their individual goals of moving as quickly as possible to a common destination. A form of emergent cooperative behavior not based upon an experimental precondition, but rather based upon a need to solve an unanticipated problem would have been a more significant contribution to the swarm-bots initiative; especially considering one of its potential application domains is in real-world search and rescue operations [26].

Also as part of the swarm-bots research initiative, Baldassarre *et al.* [2] presented a set of experiments for investigating emergent cooperation in the form of flocking behaviors. The task was for a group of simulated robots to move in the least amount of time towards a light target. An artificial evolution process governing the derivation of robot behaviors over many task trials elucidated emergent forms of situated and specialized behavior that allowed the group to act as a single unit. In many cases the individual robots displayed complementary behaviors in order to form a cooperative group behavior to satisfy their task. Groups consisted of four simulated Khepera robots [22], where all experiments were conducted in simulation using an extended version of the Evorobot simulator [24]. At the beginning of each task trail the four robots were placed in random positions and orientations within a square walled environment, and a light source elsewhere in the environment was switched on. The fitness function of the robot group was based upon how compact the group was with respect to the relative distances between the robots, and the average speed of the robots as they moved towards the light source. The fitness of the robot group for a given task trial was determined with respect to each robots performance in these two aspects of the fitness function. This fitness function produced aggregation of groups, and yielded the emergence of several cooperative strategies. In all executions of the evolutionary process, individuals evolved some form of cooperation to be able to form groups, maintain group coherence, and move uniformly towards the light source. The different group strategies assumed different formations in one of three different classes of strategies, termed *flock*, *amoeba*, and *rose* by the authors. The flock class of group strategies was a particular example where behavioral specializations emerged. This strategy required that different individuals were able to assume and maintain qualitatively different functions in the group. The flock strategy emerged in few executions of the evolutionary process, where as the simpler set of strategies in the amoeba and rose class of strategies emerged more often though were less successful due to a lack of behavioral specialization in the formation of group strategies.

Several forms of cooperative behavior were synthesized via techniques of artificial evolution, though cooperative behaviors using functional specialization performed the best according to the evaluation criteria. The authors argued that functional specialization evolved due to the need to reduce the interference between conflicting sub-goals such as the need to turn and move toward the rest of the group and toward the light target. The problematic aspect of these experiments was that they aimed to create effective cooperative behaviors purely through the use of artificial evolution. This made analysis of the emergent behaviors difficult, so it is known that behavioral specialization played a key role in the formation of cooperative strategies but it remains unknown how behavioral specialization emerged in these experiments.

III. Future Directions

The aim of this survey was not to provide an exhaustive list or compilation of all research in swarm-based systems, but rather to highlight prevalent examples of when emergent cooperation facilitates a solution that would not otherwise be attainable or as efficient without cooperative behavior. The theme of the survey, argued from these research examples, that the majority of research into emergent cooperative swarm-behavior utilizes simple or limited task domains. Though, given that the mechanisms leading to emergent cooperation in biological systems such as ant and termite colonies are still largely a mystery, the use of simple forms of cooperation and limited task scenarios is justified. It is evident from the literature that use of swarm systems and their accompanying biologically inspired design methodologies is deemed by many researchers, to be an effective means for investigating the conditions under which cooperation emerges. This is especially true in simulations where the effects of parametric changes on emergent cooperative behavior can be seen in a relatively short space of time. Unfortunately current swarm systems lack proven methodologies that allow the transfer of simulated biological mechanisms to algorithms that can be used effectively in real world decentralized systems. Additionally, the use of evolutionary computation was highlighted in many cases as being an effective means for the derivation of cooperative behavior. Though, use of artificial evolution is still largely in a stage of infancy, so evolution of cooperation is currently limited to simple forms in swarms comprised of computationally very simple individuals.

In the results outlined and research reviewed, several key open problems were identified. These problems were not constrained by the nature of swarm systems themselves, but rather by the infancy of the biologically inspired design mechanisms and the distinct lack of analytical methods and techniques. In each set of results surveyed, each researcher was using their own approach and development platform for the synthesis of cooperative behavior as well as different methods for the interpretation, evaluation and analysis of emergent cooperative behavior. It is obvious that if emergent cooperative behavior derived from swarm systems is to be used to any great benefit, especially in large scale distributed real-world systems, then it is important that future research address certain open problems. Specifically, if the notion of emergent cooperation is to gain any maturity and credence as a viable means of problem solving, then results yielded must be quantifiable and comparable with traditional methods of achieving collective or otherwise multi-agent goals. Ideally, proven design methodologies for achieving desired emergent cooperation must be scalable and transferable to a counterpart real-world application domain, meaning that such methodologies would need to be defined by algorithms and methods of analysis that are equally applicable in the physical world.

Thus the most promising research avenues for future progress to be made in swarm systems are those that define a structured and interdisciplinary approach in developing theories, and design methodologies for evaluating the validity of emergent cooperation. Even though advantages of biological inspired design such as redundancy, scalability, and minimalist component design have been utilized to great lengths in swarm-based systems, the true potential of a biological inspired methodology is often overlooked. That is, in many swarm systems with notable exceptions such as the *ant-based system* [11]; biologically inspired methodologies are used only to demonstrate concepts such as self-organization, and emergence and their apparent contribution to 'swarm intelligence'. Rarely, are swarm methodologies used for formulating and synthesizing effective forms of collective behavior, such as cooperation, that can be evaluated or otherwise conform to a standardized benchmark. This elucidates the problem that there currently exists no standardized benchmark or method for evaluation of, or otherwise classifying emergent cooperative behavior in swarm systems. Additionally, when emergent cooperation in swarm systems is achieved it is rarely tested concurrently in a real world problem domain and results are not compared with more traditional approaches that do not utilize a biologically inspired design approach to achieve group or global level goals. The comparison of results using emergent cooperation with those attained using more classical distributed artificial intelligence design approaches is an aspect that is missing from many current research endeavors, and should form a greater part of future research if the notion of emergent cooperation as a means of problem solving is to gain credibility.

Given the early stage of research and development of swarm systems and the relative infancy of the notion of emergent cooperation as a means of solving global or group level problems, it is justifiable that standardized methods for deriving, testing, proving the convergence of, and evaluating emergent cooperative behavior do not yet exist. Though, much success has already been achieved using relatively simple synthetic approaches for the design of emergent cooperation that included a disparate array of preliminary methods for behavioral analysis. Thus, if particular key problems highlighted throughout this article are focused upon as subjects of future research, then the concept of emergent cooperation as a means of problem solving derived within the context of a swarm based system, would no longer be restricted to highly experimental and abstracted methodologies implemented as constrained simulations.

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