Swarm Cognition and Artificial Life

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Abstract. Swarm Cognition is the juxtaposition of two relatively unrelated concepts that evoke, on the one hand, the power of collective behaviours displayed by natural swarms, and on the other hand the complexity of cognitive processes in the vertebrate brain. Recently, scientists from various disciplines suggest that, at a certain level of description, operational principles used to account for the behaviour of natural swarms may turn out to be extremely powerful tools to identify the neuroscientific basis of cognition. In this paper, we review the most recent studies in this direction, and propose an integration of Swarm Cognition with Artificial Life, identifying a roadmap for a scientific and technological breakthrough in Cognitive Sciences.

1 Introduction

What do ants and neurons have in common? A bit of reasoning reveals that they share more than one would intuitively think. An ant is part of a colony, much as a neuron is part of the brain. An ant cannot do much in isolation, but a colony is a highly resilient adaptive system. Similarly, a neuron is individually able just of limited interactions with other neurons, but the brain displays highly complex cognitive processes. In other words, both ants and neurons behave/act in perfect harmony with other conspecifics/cells to accomplish tasks that go beyond the capability of a single individual. Self-organisation is the common mechanism that allows simple units—e.g., ants and neurons—to display complex spatio-temporal patterns. As a consequence, colony behaviour and cognitive processes can be explained in terms of self-organising rules of interaction among the low-level units and their environment. By describing the behaviour of ants, Aron *et al.* recognise that "while no individual is aware of all the possible alternatives, and no individual possesses an explicitly programmed solution, all together they reach an 'unconscious' decision" [1]. This is particularly true also for neural systems, where the relevance or the meaning of the self-organised pattern is not found at the individual level, but at the collective one.

Recent work recognises this close relationship between brains and swarms [2–4], giving birth to a novel approach in the study of collective intelligence and computational neuroscience. This is the *Swarm Cognition* approach, which aims at encompassing the above mentioned disciplines under a common theoretical and methodological framework. In this paper, we suggest that Artificial Life can give an essential contribution to Swarm Cognition studies. In fact, by synthesising distributed models of cognitive processes through ALife techniques, it could be possible to discover the underlying mechanisms common to swarms and to the vertebrate brain.

In the following, we will outline the background of Swarm Cognition, identified in studies of self-organising behaviours and in computational neuroscience (see Section 2). We continue in Section 3 by reviewing two recent studies that belong to Swarm Cognition, and we finally discuss how ALife can contribute in this direction in Section 4. Section 5 concludes the paper.

2 Background

The foundations of Swarm Cognition has to be found in the study of self-organising systems, particularly biological systems that can display cognitive behaviour, which are treated in Section 2.1, and in computational models of brain functions, discussed in Section 2.2.

2.1 Self-Organisation in Biological Systems

Self-organising systems can be found in living and non-living matter. Self organisation refers to a spatio-temporal pattern (e.g., a collective behaviour or a physical structure) that is not explicitly programmed in each individual component of the system, but emerges from the numerous interactions between them. Each component only follows simple individual rules, which are performed with approximation on the basis of local information only, without any global map or representation [5]. Self-organised behaviour has been demonstrated in real biological societies, particularly in insects, but also in fish, birds and mammals, including humans (for some recent reviews, see [5–8]).

The basic ingredients of self-organisation are often recognised in *multiple interactions*, which generate *positive* and *negative feedback* mechanisms that allow the system to amplify certain *random fluctuations*, and to control the evolution of a coherent spatio-temporal pattern. A self-organising system is therefore able to achieve and sustain a certain spatio-temporal structure despite external influences [5]. A slightly different view of self-organisation focuses on its dynamical aspects, by describing the self-organising system as a complex dynamical system close to a bifurcation point. This means that the system, upon variation of some control parameter—e.g., temperature or chemical concentration—rapidly changes presenting new spatio-temporal patterns—e.g., a new type of collective behaviour or physical structure. This latter view of self-organisation is particularly relevant for Swarm Cognition studies. Indeed, it suggests that decision-making processes can be seen as the result of a bifurcation of a complex dynamical system. This system is formed by simple units that interact to produce the global spatio-temporal pattern, which results in the self-organised decision. There is clearly room to include in this definition also distributed processes that take place in the vertebrate brain. Here, the system units are individual neurons or neuronal assemblies, and the interactions are in form of inter-neuron communication. As we shall discuss in the next section, the dynamical and self-organised aspects of cognition are recently acquiring more and more attention.

2.2 Computational Neuroscience

Modelling of brain regions is not a novel endeavour: a long research tradition attempted to shed some light on the mechanisms at the basis of human reasoning, not without any success. Early in the mid fifties, Connectionism postulated the use of artificial neural networks (ANNs) as tools to study cognitive phenomena, without the need of knowledge representation, symbols and abstract reasoning [9]. With the advent of Computational Neuroscience, researchers have started to recognise the exquisitely dynamical traits of cognitive processes [10]. Dynamical systems theory is recently acquiring more and more attention in cognitive sciences as it can give explanations of cognitive phenomena while they unfold over time. Concepts like "attractor" and "bifurcation" start to be commonly used, and dynamical models are developed—just to name a few—to give new answers to classic psychology debates such as the A-not-B error in infant reaching [11], or to account for intrinsically dynamical processes such as inter-limb coordination [12, 13]. To date, connectionist models are merged with the dynamical systems approach, recognising that cognitive processes are the result of a complex web of interactions in which both time-dependent and topological factors play a crucial role. In [14], Deco *et al.* propose the study of brain functional organisation at different space-time description levels, in order to understand the fundamental mechanisms that underpin neural processes and relate these processes to neuroscience data. However, so far there has been only limited room for holistic explanations of cognitive processes at different levels of description. Neither the relation with embodiment and environmental interactions has been thoroughly investigated. As we shall see in the following, the Swarm Cognition approach, by drawing parallels between swarm behaviours and the vertebrate brain, targets distributed processes in which cognitive units act in interaction with their environment, therefore attempting an holistic explanation of the phenomena under observation.

3 Case Studies: From Collective Intelligence to Cognition

Animal groups often display collective behaviours that allow to regulate the activities of the group maintaining a coherent organisation. In [2], Couzin observes that the dynamics of group behaviour show interesting similarities with those of cognitive processes in the brain. Multistability, non-linear responses, positive and negative feedback loops, population averaging and consensus decision-making (winner-takes-all) are the ingredients of cognitive process both in animal groups and in the brain. Recent studies argue that the massively parallel animal-to-animal interactions which operationally explain collective processes of natural swarms are functionally similar to neuron-to-neuron communication which underlie the cognitive abilities of living organisms, including humans [3, 4]. In this section, we briefly review these studies highlighting the main features of Swarm Cognition.

3.1 Swarm Cognition in Honey Bees

The nest site selection behaviour of honey bees *Apis mellifera* is the starting point taken by Passino *et al.* for a comparison between the decision-making abilities displayed by the swarm and the cognitive functions of primate brains [3]. Honey bees select a new nest site through a self-organising process, which is mainly based on a positive feedback mechanism that differentially amplifies the perceived quality of discovered nest sites. Scout bees explore the area surrounding the swarm in search of valuable sites. When they discover a potential nest that has a *supra-threshold* perceived quality, they return to the nest and perform a *waggle dance* to recruit other scouts. The higher the perceived quality, the longer the waggle dance, the stronger the recruitment. In this way, the differences between low quality nesting sites are amplified, allowing to quickly discard poor sites in favour of the better ones. When a sufficient number of scouts has been recruited to a nesting site (i.e., a *quorum* is reached), a second phase is triggered that leads to the lift-off of the entire swarm.

It is important to notice that the selection of the best nest site is not performed by individual bees that directly compare different options by visiting different sites. Neither it is based on the comparison of different waggle dances. The competition between sites is performed at the level of the group through recruitment and quorum sensing, and not at the level of the individual bee. In this respect, a strong parallelism with brain functions can be recognised. Scout bees perform functions similar to individual neurons in the brain. Waggle dances are analogous to action potentials, and the threshold in the estimated quality of a discovered nest corresponds to the neuron activation threshold. The parallelism between swarm and brain goes beyond these similarities, including lateral inhibition, feature detection and attention. By developing a model of nest site selection, tests have been performed to assess the discrimination abilities between different sites, as well as the ability of the swarm as a whole to discard distractors and focus the attention on the highest quality site [3].

3.2 Decision-Making in Brains and Insect Colonies

The work of Marshall *et al.* [4] goes a step further. They again focus on nest site selection in rock ants (*Temnothorax albipennis*) and in honey bees, and show that it has the same properties of diffusion models used to characterise decision-making in the cortex [15]. Diffusion models describe the accumulation of evidences trough time during a decision-making process as a random walk with normally distributed step size (Wiener process or Brownian motion), subject to a constant drift toward the better choice. When a threshold is passed toward one or the other alternative, the decision is taken.

The remarkable fact is that similar diffusion models provide a statistically optimal speed-accuracy tradeoff in decision-making, which reflects the tension between the need to take a quick decision and the need to wait until enough evidence is accumulated in favour of one or the other option. In fact, by varying the decision threshold, the model can account for quick but unsafe decisions, or for more conservative but time-demanding ones. The speed accuracy tradeoff is well known from psychological experiments in humans and animals, and has been also recognised in the nest site selection behaviour of rock ants: under stormy weather conditions, ants lower their decision threshold (i.e., the quorum necessary to select a site), therefore performing a quick decision at the expense of a higher error rate [16].

In [4], the authors analyse a model of the ants nest site selection, as well as two models of the same process performed by honey bees, also described above. These models differ mainly in the possibility for scouts of direct switching of commitment between alternative sites, without passing through an "uncommitted" state. The model that allows direct switching corresponds to a diffusion model, accounting for statistical optimality of the nest selection behaviour, and suggesting that neural and swarm decision-making can be explained by functionally similar mechanisms.

4 The Artificial Life Approach

In the previous section, we have described how comparative studies of cognitive processes and swarm behaviours highlight surprising similarities. We believe that this is not a fortunate case, and we suggest that similar comparisons should be further developed, in search of common working mechanisms. This is the goal of Swarm Cognition studies that involve the observation of the biological reality. In this paper, we propose Artificial Life as a complementary approach to the investigation of Swarm Cognition. ALife is intimately connected to Cognitive Sciences. Bedau recognises this as he notices that "one of the fundamental open problems in artificial life is to explain how robust, multiple-level dynamical hierarchies emerge solely from the interactions of elements at the lowest-level. This is closely analogous to the problem in cognitive science of explaining how cognitive capacities ultimately emerge from the interactions of non-cognitive elements like neurons" [17].

We propose the development of an ALife approach to Swarm Cognition, aiming at improving our understanding of the mechanisms behind cognitive processes by synthesising such processes in artificial systems. By paraphrasing Langton [18], we claim that ALife and Swarm Cognition can contribute to Cognitive Sciences by locating *cognition-as-we-know-it* within the larger picture of *cognition-as-it-could-be*. This means that the ALife approach to Swarm Cognition, by building bridges between computational neuroscience and swarm intelligence, searches for the underlying mechanisms of cognition being inspired, rather than constrained, by the biological reality.

4.1 Beyond Connectionism

A first contribution of ALife to Swarm Cognition is providing explanations of cognition as the result of self-organising processes through computational models. Indeed, there is no doubt that cognitive processes involve a massive amount of neuron-to-neuron interactions. There is also no doubt that neurons are organised in assemblies of coherent activities, and that they are spatially and functionally segregated in different brain areas. It is anyway difficult to unveil causal relationships between neurophysiological phenomena and cognition, without reducing the latter to the former. The Swarm Cognition approach is expected to shed light on such complex issue by explicitly searching for the emergence of measurable phenomena from the interaction of low-level *cognitive units*. These cognitive units should not necessarily be related to biological reality—e.g., neurons, neuronal assemblies or populations—but may well be closer to a bee or to a generic artificial agent.

The main goal of these studies should be the identification of the mechanisms underlying cognitive processes, as a result of the dynamical interactions among cognitive units. The simulated approach brings these activities closer to computational neuroscience, and cross-fertilisation between the two disciplines should be promoted whenever possible, in the attempt to complement neruophysiological models and fit, at least qualitatively, experimental data.

4.2 Embodiment and Swarm Robotics

A distinctive feature of ALife is the attempt to study how life occurs not only in computer simulation, but also in the physical world. "Wet" ALife seeks the synthesis of living systems out of biochemical substances. Apart from this, robotics is the other field of confrontation with the physical world. In Bedau's view, (evolutionary) robotics "is artificial life's most direct overlap with cognitive science, as its aim is to synthesize autonomous adaptive and intelligent behavior in the real world" [17]. When adaptive behaviour is performed by a swarm of robots, we deal with a *Swarm Robotics* system, characterised by limited abilities at the level of the individual robot, which can anyway perform complex tasks by coordinating in a group.

There are multiple reasons that justify the swarm robotics approach to cognition. First of all, it is important to stress the relevance of using robots to study cognitive processes. Robots are artifacts with a physical body situated in the physical world, with physical sensors and actuators to perceive and act within their environment. The embodiment of the robots is a very important aspect for the study of cognitive behaviour, which is not the result of "reasoning" alone, but is rather the result of the dynamical interactions between brain, body and environment. Robots therefore are excellent tools to study such brain-body-environment dynamics and their bearing on the emergence of cognitive abilities such as categorisation, decision making, attention and learning [19].

Additionally, a peculiar feature of Swarm Robotics systems is the transfer of behavioural complexity from the individual to the interactions among individuals. Brought to the limit, this vision sees robots as neuron-like devices that can move in the environment and interact, physically or trough communication, with other robots, while bringing forth complex cognitive processes as a whole. Within the Swarm Cognition framework, this transfer of complexity from the individual behaviour to the interactions among individuals is fundamental to understand how cognitive processes can be supported by distributed systems. Swarm Robotics is therefore the only mean to study self-organisation in embodied and situated systems. Each robot is a cognitive unit, in this case, playing either the role of the individual insect in a swarm, or the role of a neuron or an assembly in the brain. In our opinion, all these aspects make Swarm Robotics the most appropriated method to instantiate the Artificial Life approach to Swarm Cognition.

4.3 Bridging the gap between behaviour and cognition

Comparative studies in Swarm Cognition can pinpoint the relevant mechanisms that support cognition, a significant breakthrough in Cognitive Sciences. The ALife approach offers the possibility to synthesise cognitive process in artificial brains as well as in artificial swarms. With such a dual approach, it is possible to study similar problems, such as decision-making or attention, in search of common mechanisms. Similar discoveries in artificial systems may well be generalisable to natural ones, when some biological plausibility has been preserved into the models.

Additionally, the knowledge acquired in Swarm Cognition studies could also be integrated in a single experimental scenario in which a swarm of robots is governed by neurocomputational controllers. In this way, the ALife approach to Swarm Cognition is expected to advance the state of the art in robotics and computational neuroscience. In fact, by integrating neurocomputational controllers in swarm of robots, an highly complex system could be synthesised, composed of three different organisational levels hierarchically stacked, from the neurocontroller internal dynamics, through the embodied cognition displayed by the individual robot, up to the cognitive processes displayed by the group dynamics. In this way, we could have a physical realisation of multiple-level dynamical hierarchies that truly generate cognition from the bottom-up.

5 Conclusions

In this paper, we have introduced Swarm Cognition as a multidisciplinary research field that bridges studies in collective intelligence and computational neuroscience under a common theoretical and methodological framework. We suggest that ALife can give a significant contribution, by developing synthetic models of *cognition-as-it-could-be*. This concerns both simulated models of the brain and swarm robotics systems. The goal is understanding how cognitive processes are brought forth as transient dynamics emerging from massively parallel interactions among cognitive units, be they simulated neurons or physical robots.

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