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Editorial

Recent Advances in Swarm Robotics Coordination: Communication and Memory Challenges

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Swarm robotics research has been present for some decades, providing nature-inspired algorithms in swarms of robots. During this time, many different algorithms have focused on specific tasks, such as coordination, cooperation, organization, division of labor, or task allocation, among others. However, basic concepts, such as the use of communication, collective memory, or optimized coordination, are still important challenges when designing swarms of robots.

One of the most critical design steps is the communication mechanics of the group. Communication within the swarm refers to any kind of interaction among robots, in which information about states, actions, or intentions of agents is shared across the swarm. According to [1], inter-agent communication in swarm robotics can be split into: stigmergy, interaction via state, or direct communication. Another distinction can be highlighted in the case of direct communication. Essentially, we can differentiate between direct communication semantics and codes that are handcrafted by the researcher or communication semantics that arise from automatic controller design methods. In the latter scenario, it is said that communication emerges. Clearly, the researcher still must design and establish the communication means and resources, but the semantics and the information relevant to the emerged communication are a result of optimization processes. Within this context, communication can also be identified as abstract or situated communication [2–6]. However, nowadays, many aspects remain unsolved. For example, how does the communication emerge? How should it be implemented? To what extent does increasing or reducing the communication capabilities improve or worsen the swarm behavior?

Another important unsolved aspect is collective memory. Remembering information is a fundamental aspect of cognition, present in numerous natural systems. The ability to store and later use information is essential for a variety of adaptive behaviors, including integration, learning, generalization, prediction, and inference [7]. Moreover, memory allows behavior changes based on previously learned situations. Many living organisms remember penalties or rewards, relying on these memories to repeat or avoid similar situations. However, what if the individual does not hold the required information itself? Is the group capable of collectively creating a memory? These are aspects that also remain unsolved.

In recent decades, several works have focused on these communication and memory challenges for the coordination of swarms of robots [8–12]. In this editorial, we refer to nine specific works dealing with these aspects. The highlighted manuscripts approach these problems from several perspectives (control theory, statistical analysis, machine learning, or deep learning) and types of robots (terrestrial, aerial, or underwater robots). Regardless of the approach, they all share a common objective, to increase the actual understanding on collective robot control and coordination.

Specifically, Sendra and Gutiérrez analyze the evolution of different kinds of abstract and situated communications in collaborative environments [13]. The objective is to maintain the same neural structure to develop controllers that adapt to different tasks. The neural controllers are optimized using Separable Natural Evolution Strategies (SNES) [14]. The

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semantics of the communication are undefined at the design phase and they correspond to the evolution process and fine-tuning of the neural controller, based on the communication information that becomes relevant for the task. The manuscript confirms that the evolution guides the communication towards very different mechanics and semantics, although the neural controllers are architecturally identical. Nonetheless, the evolved systems are scalable and robust under predefined perturbations.

On the other side, Campo et al. investigate how individuals without memory capabilities may display collective memory [15]. They gain inspiration from the Pavlov experiment and propose an aggregation experiment on a swarm of robots. Within the experiment, the group encodes and recovers information that is not independently stored on the individuals of the swarm. On the contrary, the information is stored over specific spatial configurations of the group. The results show that a swarm of robots can have a memory of its own, independently of the internal state of its members. With simple agents and behavioral rules, the robots learn to associate different stimuli with spatial information.

Focusing on planification, Ahmed et al. develop a distributed path planner for multi-robot systems with a mechanism based on priorities [16], by integrating Particle Swarm Optimization (PSO) [17] and the Bresenham algorithm [18]. In their proposal, PSO is used to generate the optimal trajectory, with a multi-objective fitness function based on energy consumption and movement risk. The Bresenham algorithm is used for ensuring the full coverage of the operational area. The communication between robots is performed with each other in an ad hoc manner, and it is only used to share position and location among themselves.

Extending the communication assumptions raised in the previous work, Coquet et al. propose a new method inspired by flocking algorithms and PSO, named the Local Charged Particle Swarm Optimization (LCPSO) algorithm [19]. In this case, the authors control a swarm of robots with communication constraints between agents. The authors test the algorithm in a formation scenario with source heading, where the positions of the center of gravity and attractors guide the swarm. Moreover, based on tunable parameters, the algorithm controls the swarm with minimal communication or interaction, achieving a stable formation which is invariant to time.

Nonetheless, limited communication is also exploited in [20]. The authors propose a distributed and asynchronous approach to simultaneous task assignment and path planning. The authors refer to it as Hierarchical Task Assignment and Path Finding (HTAPF), exploiting a hierarchical representation of the locations where tasks must be executed. The proposal combines a bio-inspired collective decision-making process and a search-based path planning. The algorithm is decentralized for both tasks, being robust to limited communication and robot failures and scalable to different environments and group sizes. Task allocation supports multiple hierarchical decision levels and a utility function that directly considers the cost of motions.

By dividing the level of competences, the authors of [21] develop a macroscopic foraging behavior for collectively transporting objects. The authors define two microscopic behaviors, both for displacement and collision avoidance. The robots adapt to unseen changes in the environment, operating coherently with its initial goal. The authors verify that the behavior definition on the microscopic system does not only simplify the learning of the global system, but it also provides a way to adjust microscopic behaviors without significant macroscopic changes.

Based on the same concepts of division of behaviors, a multilayer architecture is presented in [22]. The different layers focus on trajectory planners, obstacle avoidance algorithms, and decision-making methods. Every layer provides the swarm with the necessary technology to solve problems arising from coordinated and unsupervised navigation. Moreover, each layer includes a set of methods that increase the robustness of the architecture, by developing redundant implementations and control loops. The layers are later combined to allow the coordinated navigation of a robot swarm in different environments.

Control theory has typically been used for optimizing the emergence of order in swarms. As a step further, [23] proposes a new algorithm that optimizes the swarm movements with respect to interaction requirements. The authors propose a systematic methodology, combing control theories and statistical analysis for its purpose. In their proposal, every individual is considered an egalitarian system that focuses on the rules applied to the nearest neighbour. The results indicate that by reducing the interaction between the individuals, a faster convergence of the group task is achieved.

In the same direction, Aznar et al. provide the microscopic design of two behaviours, Slant beacon deployment (SLABE) and Sematectonic Pheromone Deployment (SEPHE), to analyse how the number of agents influences the deployment of the macroscopic behaviour [24]. For this purpose, they use a virtual stigmergy system, assuming a local positioning mechanism in a mesh network. Consistent with [23], the authors find that, for complex environments, the less informed behaviour achieves the task execution in a similar way to that of the informed approach, but with a lower energy and computing cost.

As can be observed, all the manuscripts presented in this editorial point to the direction of improving swarm behaviour and control, with the aim of reducing communication costs and interaction to a minimum. Moreover, these new concepts based on optimization will continue growing until a new complete approach of multi-agent self-organization emerges. Therefore, in the following years, collective communication and memory paradigms will arise, where a high number of heterogeneous optimization algorithms will coexist to improve the swarm coordination and its distributed control.

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