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Soft Computing for Swarm Robotics: New Trends and Applications

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ABSTRACT

Robotics have experienced a meteoric growth over the last decades, reaching unprecedented levels of distributed intelligence and self-autonomy. Today, a myriad of real-world scenarios can benefit from the application of robots, such as structural health monitoring, complex manufacturing, efficient logistics or disaster management. Related to this topic, there is a paradigm connected to Swarm Intelligence which is grasping significant interest from the Computational Intelligence community. This branch of knowledge is known as Swarm Robotics, which refers to the development of tools and techniques to ease the coordination of multiple small-sized robots towards the accomplishment of difficult tasks or missions in a collaborative fashion. The success of Swarm Robotics applications comes from the efficient use of smart sensing, communication and organization functionalities endowed to these small robots, which allow for collaborative information sensing, operation and knowledge inference from the environment. The numerous industrial and social applications that can be addressed efficiently by virtue of swarm robotics unleashes a vibrant research area focused on distributing intelligence among autonomous agents with simple behavioral rules and communication schedules, yet potentially capable of realizing the most complex tasks. In this context, we present and overview recent contributions reported around this paradigm, which serves as an exemplary excerpt of the potential of Swarm Robotics to become a major research catalyst of the Computational Intelligence arena in years to come.

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1. Introduction

Swarm Intelligence (SI) is a paradigm attracting a lot of attention in the Computational Intelligence and Operations Research community. Briefly explained, SI refers to the complex collective behavior of self-organized and decentralized systems, typically composed of a spatially distributed – and often large – population of individuals, or agents. These agents interact with each other and with the environment in different but simple ways, coordinating their actions throughout the iterated application of local behavioral rules, thereby making the swarm inherently robust, effective, and flexible enough to undertake several tasks.

From the algorithmic perspective, SI comprises techniques widely used nowadays in academia and industry for solving complex optimization problems. To this end, SI based solvers harness the existence and proven efficiency of distributed intelligence in nature phenomena, such as the behavioral patterns of bats [1], fireflies [2], bees [3] or cuckoos [4], as well as the mechanisms behind genetic inheritance [5] and bacterial foraging [6], among many others [7]. A plethora of scenarios have so far resorted to SI when addressing optimization, inference and prediction tasks. Some of the most common ones are transport and logistics [8,9], medicine [10,11] or graph mining [12,13].

Among them, a specific research topic protrudes in the literature of the last decade: Swarm Robotics (SR) [14,15]. Specifically, SR denotes the application of SI methods to scenarios where computational agents represent physically implemented or simulated robotic devices. The focus of SR is to thoroughly analyze how a swarm comprised of relatively simple robots can coordinate to collectively accomplish different kind of goals that are out of the common capabilities of a single robot. The main advantages of using SR systems are:

- *Robustness*: due to the distributed nature of the swarm, the failure of a single robot does not compromise the integrity and operation of the remaining robots in the swarm.
- *Scalability*: the addition of new robots to the swarm can be made incrementally (without reconfiguring the entire population), and does not penalize the overall computational efficiency of the swarm when undertaking the task at hand.
- *Parallelization*: complex control is achieved through simple yet concurrently held interactions between the members of the swarm.

Algorithms and methods relying on SR have been so far excelled over a wide range of complex real-world problems, such as localization [16,17], disaster rescue missions [18,19], agricultural foraging and seeding [20,21] or scenery mapping problems [22,23]. As evinced by this noted activity around the topic, interests in SR are

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manifold, and constitute nowadays a popular topic that lays at the core of many contributions in the literature.

This editorial introduces a special issue organized around the latest advances and applications in the areas of SI and SR from two different perspectives: new theoretical advances in distributed computational intelligence and their application to real-world problems. After a strict review process of the submissions received for this special issue, twelve papers were finally accepted. All these contributions cover a wide range of algorithmic and implementation aspects, which are presented and discussed in the remainder of this manuscript. We will conclude this introductory article with a closing note calling for further efforts around SR and SI, which both face an exciting future full of challenging research directions to be addressed.

2. An Overview of this Special Issue

The contributions included in this special issue address a variety of heterogeneous topics within the field of SR, such as the localization of certain targets [24–26], organization of drones in rescue missions [27] or the reconstruction of scenarios through collective information gathering [28]. Moreover, theoretical aspects as segregation of swarms [29], path planning problems [30] and parameter tuning [31] have also found their place in this volume. In regards to algorithmic approaches, evolutionary methods such as Genetic Algorithms [32] and SI solvers such as Particle Swarm Optimization [29,25,27], Ant Colony Optimization [33], Multiverse Optimizer [30] and Whale Optimization Algorithm [34] have prevailed among the contributions discussed in detail in what follows.

To begin with, Alfeo et al. [24] consider in their study the problem of discovering static hidden targets in not homogeneous environments thanks to the use of a swarm of small dedicated Unmanned Aircraft Vehicles (UAVs). The goal of their research work is to minimize the total time spent by the UAVs to discover targets. In order to efficiently tackle this problem, authors propose a coordination approach combining three biologically inspired mechanisms: stigmergy, flocking and evolution. For assessing the performance of the proposed method, a comparison with six additional literature approaches is conducted over three synthetic and three real-world scenarios.

In their contribution [31], Garcia-Aunon and Barrientos-Cruz claim that robotic swarms are controlled by complex behaviors, which usually require tuning a wide set of parameters controlling the behavior of the swarm. Without a doubt, fine tuning these parameters can become a time-consuming task, eventually causing a great impact on the autonomy of the whole swarm. Furthermore, external parameters not configurable by the designer could also exist, such as the maximum number of robots or the work area. These evidences and solid facts confirm that the parameterization depends stringently on the scenario at hand. Bearing this issue in mind, authors of [31] propose two different approaches for the optimal configuration of controls of aerial robotic swarm with a highly dimensional configuration space.

Another interesting work can be found in [28], where Khaluf and Simoens tackle the problem of gathering information about the spatial distribution of a specific environment using a simulated robotic swarm. This particular application has a notable social interest, as it can model search and rescue missions, or specific scenarios in precision agriculture. Furthermore, due to the limited on-board capabilities associated to real robots, authors impose additional restrictions on the formulated problem under the so-called *limited sampling budget* concept. Due to the existence of this constraint, the proposed method aims at maximizing the statistical quality of the collected sample, while, at the same time, the number of obtained samples must be minimized. To reach this challenging objective, a collective sampling controller (*CSC*) approach is proposed, which relies on three phases: exploration, detection, and exploitation.

In [30], Jain et al. elaborate on a classical problem in SR, which has regained momentum lately fueled by aerial-to-ground communications support, security or disaster management, and other applications alike: path planning in aerial swarms. This study gravitates on the improvement of the performance of the whole swarm of UAVs by developing sophisticated communications, allowing them to coordinate dynamically. Specifically, the optimization problem casted in this research work contemplates three-dimensional environments, and is efficiently tackled by the application of a Multiverse Optimizer. The implemented system is tested over three different maps and compared to other similar optimization heuristics, such as the Glowworm Swarm Optimization and Biogeography-based Optimization.

Innocente and Grasso [27] demonstrate in their work how SR is a feasible approach for autonomously and collaboratively battling against the spread of wildfires. This highly interesting application can be materialized thanks to the self-coordinating behavior of robotic swarms. Thus, the authors of this work design and develop a self-organization technique for the swarm in combination with a physics-based model of fire propagation. The collaborative mechanism relies on Particle Swarm Optimization (PSO, [35]) suitably adapted to robots working within physical dynamic environments of high severity and frequency of change. Several insightful conclusions are drawn from the conducted experimentation related to the scalability of the system or the resilience of the whole swarm to robotic failures at its core.

Rebouças Filho et al. [32] face a recurrently studied problem in robotics: trajectory singularity in robots manipulators. In their work, authors propose two different methods for trajectory control, both based on Genetic Algorithms. The main advantage of the proposed approaches is that possible singularities are corrected without the need of computing the whole trajectory, making the solution independent of the manipulator's physical structure.

On the theoretical side, Inácio et al. [29] underscore the idea of segregation in robotic swarms. This concept is important for maintaining similar robots in cohesive groups, while robots with different features or objectives are kept separated. This behavior is particularly desirable to assign specific tasks according to certain characteristics of each group. Authors of this manuscript present a decentralized approach for segregating heterogeneous groups of robots which are randomly distributed on the environment. The developed method consists of a navigation strategy inspired on the PSO heuristic solver, in combination with an Optimal Reciprocal Collision Avoidance algorithm to keep the group cohesion in an organized and physically safe manner.

Jain et al. [25] also consider the PSO in their contribution. In this case, a PSO based multi-robot cooperative approach for multiple odor source localization is presented. To bridge the gap between the real-time experiments and simulation, sensor odometric error along with localization error in robot positioning is considered. Furthermore, the well-known CFD software Ansys Fluent is used to model the odor plume dispersion in the 3D indoor environment.

Landmark detection and landmark matching is studied in [26] through the use of Autonomous Underwater Vehicles (AUV). For conducting this challenging task, the behaviour of AUVs is hybridized with Remotely Operated Vehicles (ROV), deploying an heterogeneous albeit cooperative mesh. In this work, authors employ data recorded at Gran Canaria (Spain) for testing the image registration and multisensor registration features of the whole system.

Biped robot gait stability is addressed in [34], which continues a profitable story of related contributions springing from the literature on robotics along the last decade. In this work, authors try to find the optimal settings of the hip parameters that make the zero moment point stays in the middle of the support polygon as much as possible. To this end, an improved version of the Whale Optimization Algorithm is proposed, coined as A-C WOA. Authors focus their attention on the standard parameters of this algorithm (*A* and *C*), specifically through the variation of the first one in a non-linear and random way, and the update of the second one by applying inertia weight strategy. A comprehensive experimentation is conducted in this manuscript, where the results obtained by the A-C WOA are compared to those obtained by five alternative techniques: the naïve version of WOA, PSO, Differential Evolution, Genetic Algorithm and Salp Swarm Algorithm.

Khaluf et al. [33] present an efficient task allocation technique for robotic swarms to conduct tasks under specific time constraints. Specifically, the developed method hinges on an improved variant of the Ant Colony Optimization, which updates the pheromone trails employing the experiences gathered by the individual robots while executing their assignments. Experiments discussed in this work confirm that the proposed method properly manages the swarm for accomplishing its assigned missions by the specific deadlines in both static and dynamic simulated environments.

Finally, Abouaïssa and Chouraqui [36] showcase in their work the capability of the *Model-Free Control* and its related intelligent Proportional, Integral and Derivate (iPID) regulators to command a highly nonlinear and uncertain robotic system. For properly reach their fixed objective, authors use the proposed model for controlling the PUMA 560 Robot, which is a well-known industrial robot with six degrees of freedom.

3. Conclusion and Perspectives

This special issue sheds inspiring light on the current capabilities of distributed intelligence. The findings found by the whole group of contributors to this special issue should be regarded not only as an informed evidence of the sparkling research activity around SR and SI, but also as a symptom of the thrilling future envisioned for this field. Articles published in this special issue have applied sophisticated SI optimization methods for the efficient management of robotic swarms, yet a large branch of other SI methods remains uncharted for this application scenario. Additionally, the fast advance of the technology constantly brings us the opportunity of working with more intelligent and advanced small-sized robots, such as UAVs, which are already present in this special issue [24,31]. For these reasons, we decidedly advocate for more efforts in the near future towards the adaptation of more SI methods to the distributed management and operation of robotic swarms in the future, as well as for the consideration of the varying properties of heterogeneous robots within the swarms. It is beyond any doubt that the opportunities and benefits granted by the evolution of swarm robotics and distributed intelligence will soon surpass the limits of our imagination.

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