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A fuzzified systematic adjustment of the robotic Darwinian PSO

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ABSTRACT

The Darwinian Particle Swarm Optimization (*DPSO*) is an evolutionary algorithm that extends the Particle Swarm Optimization using natural selection to enhance the ability to escape from sub-optimal solutions. An extension of the *DPSO* to multi-robot applications has been recently proposed and denoted as Robotic Darwinian *PSO* (*RDPSO*), benefiting from the dynamical partitioning of the whole population of robots, hence decreasing the amount of required information exchange among robots. This paper further extends the previously proposed algorithm adapting the behavior of robots based on a set of context-based evaluation metrics. Those metrics are then used as inputs of a fuzzy system so as to systematically adjust the *RDPSO* parameters (*i.e.*, outputs of the fuzzy system), thus improving its convergence rate, susceptibility to obstacles and communication constraints. The adapted *RDPSO* is evaluated in groups of physical robots, being further explored using larger populations of simulated mobile robots within a larger scenario.

1. Introduction

Mimicking phenomena observed in nature has been the key to the successful development of new approaches in computational sciences (e.g., optimization algorithms [1]) and robotics (e.g., bioinspired robots [2]). Undeniably, the sciences of biomimetics and biomimicry are producing sustainable solutions by emulating nature's time-tested patterns and strategies [1]. Some examples of behavior-based collective architectures, such as ants or bees, inspire the design of novel machine-learning techniques and swarm robotics. This area of research, known as *swarm intelligence* [3,4], studies large collections of relatively simple agents that can collectively solve complex problems. These schemes display the robustness and adaptability to environmental variations revealed by biological agents.

One of the most well-known bioinspired algorithms from swarm intelligence is the Particle Swarm Optimization (*PSO*), which basically consists of a technique loosely inspired by birds flocking in search of food [5]. More specifically, it encompasses a number of particles that collectively move on the search space to find the optimal solution. A problem with the *PSO* algorithm is that of becoming trapped in sub-optimal solutions. Therefore, the *PSO* may work perfectly on one problem but may fail on another. In order to overcome this problem, many authors have suggested extended versions of the *PSO*, such as the Darwinian Particle Swarm Optimization (*DPSO*) [6], to enhance the ability to escape from sub-optimal solutions (cf., [7]). An extension of the *DPSO* to multi-robot applications has been recently proposed and denoted as Robotic Darwinian *PSO* (*RDPSO*), benefiting from the dynamical partitioning of the whole population of robots [8]. Hence, the *RDPSO* allows decreasing the amount of required information exchange among robots and therefore is scalable to large populations of robots [9].

Swarm algorithms such as the *PSO* and its extensions, including the *RDPSO*, present some drawbacks when facing dynamic and complex problems, i.e., problems with many sub-optimal solutions changing over time. The lack of the adaptability to contextual information usually observed in nature turns out to result in sub-optimal solutions that are usually overcome by using exhaustive methods (e.g., sweeping the whole scenario with robots) [10]. For instance, robots in search-and-rescue applications must be efficient in persistently searching for victims while there remains a chance of rescuing them. Although the *RDPSO* previously presented is endowed with punish–reward rules inspired on natural selection to avoid stagnation, robots may take too much time to realize that they are stuck in a sub-optimal solution or that the solution is changing over time. A good example of that may be found on

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olfactory-based swarming wherein a plume is subject to diffusion and airflow, thus making it hard to find its source (e.g., detection of hazardous gases) [11].

There are two key contributions of this work. First, a set of context-based evaluation metrics, at both the micro- and macro-level, are proposed to assess the *RDPSO* behavior. For that purpose, several concepts inherent to particle swarm techniques (e.g., exploration vs. exploitation) are further studied using two physical platforms with a phase space analysis of their motion (e.g., chaoticity). Secondly, those metrics are used as inputs of a fuzzy system so as to systematically adapt the *RDPSO* parameters (i.e., outputs of the fuzzy system), thus improving its convergence rate, susceptibility to obstacles and communication constraints.

Bearing these ideas in mind, the next section presents some previously developed works to contextualize the approach proposed herein. A brief review of the *RDPSO* algorithm, which benefits from the dynamical partitioning of the whole population of robots into multiple swarms, is given in Section 2. A set of context-based evaluation metrics to measure the collective and individual performance of robots is proposed in Section 3. Subsequently, a novel fuzzy approach to assess the more suitable merging of the evaluation metrics to systematically improve the convergence and performance of the *RDPSO* is presented in Section 4. Populations of real and simulated robots to evaluate the performance of the algorithm are then used in Section 5. Finally, in Section 6 the main conclusions are outlined.

2. Related work

Regardless of *PSO* main variants, the difficulties in setting and adjusting the parameters, as well as in maintaining and improving the search capabilities for higher dimensional problems, is still a matter addressed in recent works [12–14]. Moreover, it is proved that adaptive methods are likely to perform better than nonadaptive methods. For example, one of the most common strategies presented in the literature to solve issues in setting and adjusting *PSO* parameters is based on the stability analysis of the algorithm. In [12], the individual particle's trajectory leading to a generalized model is analyzed, which contains a set of coefficients to control the system's convergence. The resulting system is linear of second-order with stability and parameters depending on the poles, or on the eigenvalues of the state matrix. Kadirkamanathan et al. [13] proposed a stability analysis of a stochastic particle dynamics by representing it as a nonlinear feedback controlled system. The Lyapunov stability method was applied to the particle dynamics in determining sufficient and conservative conditions for asymptotic stability. However, the analysis provided by the authors has addressed only the issue of absolute stability, thus ignoring the optimization toward the optimal solution. More recently, Yasuda et al. [14] presented an activity-based numerical stability analysis method, involved the feedback of swarm activity to control diversification and intensification during the search. The authors showed that the swarm activity can be controlled by employing the stable and unstable regions of *PSO*. However, in a distributed approach such as the *RDPSO*, calculating the swarm activity implies that each robot from the swarm would need to share not only its current position, but also its current velocity with all other members. An alternative to these strategies was accomplished by merging *PSO* algorithms with fuzzy logic. Fuzzy logic was introduced in 1965 by Zadeh [15] at the University of California, Berkeley, to deal with and represent uncertainties. Despite the several possible approaches to implement an online auto-tuning system, fuzzy logic seems to be more adequate to proceed as a multiple criteria analysis tool. The strength of fuzzy logic is that uncertainty can be included into the decision process. Vagueness and imprecision associated with qualitative data can be represented in a logical way using linguistic variables and overlapping membership functions in the uncertain range. For instance, in the work of Shi and Eberhart [16], a fuzzy system is merged into the *PSO* to dynamically adapt the inertia weight of particles. Similarly, Liu et al. [17] presents a fuzzy logic controller to adaptively tune the minimum velocity of the *PSO* particles. Several other authors considered incorporating selection, mutation and crossover, as well as the differential evolution, into the *PSO* algorithm. The main goal is to increase the diversity of the population by either preventing the particles to move too close to each other and collide [18,19] or to self-adapt parameters such as the constriction factor, acceleration constants [20], or inertia weight [21].

Contrary to the multi-robot foraging approach proposed herein, all previously presented works only consider *PSO* and its main variants applied to optimization problems. Robots are designed to act in the real world where both the dynamic and the obstacles need to be taken into account. Furthermore, since in certain environments the communication infrastructure may be damaged or missing (e.g., search and rescue), the self-spreading of autonomous mobile nodes of a mobile ad-hoc network (*MANET*) over a geographical area needs to be considered. Some similar works have been recently presented in the literature. For instance, the work of Saikishan and Prasanna [22] involved the path-planning and coordination of multiple robots in a static-obstacle environment based on the *PSO* and the Bacteria Foraging Algorithm (*BFA*). As the *RDPSO* uses natural selection to avoid getting trapped in sub-optimal solutions, the one proposed by the authors enhances the local search using the *BFA*. Experimental results were conducted in a simulation environment developed in Visual Studio where the pose and shape of obstacles were previously known. However, only one target and two robots were used, thus limiting the evaluation of the proposed algorithm. Hereford and Siebold [23] proposed an embedded version of the *PSO* to swarm platforms. As in the *RDPSO*, there are no central agents to coordinate robots' movements or actions. Despite the potentialities of the physically-embedded *PSO*, the experimental results were carried out using a population of only three robots performing a distributed search in a scenario without sub-optimal solutions. Furthermore, collision avoidance and fulfillment of *MANET* connectivity were not considered.

Despite the accomplishment of other similar works, none of them introduced adaptive behaviors to overcome dynamic properties of real world scenarios. However, the behavior of robots needs to change according to contextual information about the surroundings. This concept of *contextual knowledge* needs to be taken into account to adapt swarms and robots' behavior while considering agent-based, mission-related and environmental context [24]. For example, Calisi et al.'s work [25] presented a context-based architecture to enhance the performance of a robotic system in search and rescue missions using a rule system based on first-order Horn clauses. The set of metrics used as inputs was obtained considering an "a priori" map about the difficulty levels concerning mobility and victim detection. Nevertheless, in real applications this would mean a previous knowledge about the scenario, which is not always possible and can be difficult to achieve.

The next section presents the main features of *RDPSO* to help the reader in understanding the introduction to the context-based evaluation metrics subsequently presented.

3. Brief review of the RDPSO

This section briefly presents the *RDPSO* algorithm proposed in [8] and further extended in [9]. Since the *RDPSO* approach is an adaptation of the *DPSO* to real mobile robots, five general features are developed: (i) an improved inertial influence based on