Understanding the Communication Complexity of the Robotic Darwinian PSO

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Abstract: An extension of the well-known Particle Swarm Optimization (*PSO*) 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. Although such strategy allows decreasing the amount of required information exchange among robots, a further analysis on the communication complexity of the *RDPSO* needs to be carried out so as to evaluate the scalability of the algorithm. Moreover, a further study on the most adequate multi-hop routing protocol should be conducted. Therefore, this paper starts by analyzing the architecture and characteristics of the *RDPSO* communication system, thus describing the dynamics of the communication data packet structure shared between teammates. Such procedure will be the first step to achieving a more scalable implementation of the *RDPSO* by optimizing the communication procedure between robots. Secondly, the Ad hoc On-demand Distance Vector reactive routing protocol is extended based on the *RDPSO* concepts, so as to reduce the communication overhead within swarms of robots. Experimental results with teams of 15 real robots and 60 simulated robots show that the proposed methodology significantly reduces the communication overhead, thus improving the scalability and applicability of the *RDPSO* algorithm.

Keywords: *distributed search, swarm robotics, scalability, MANET, communication complexity, routing protocol.*

I. INTRODUCTION

Communication constitutes one of the most important resources for more effective cooperation among robots and improved robust collective performance [1]. The way robots communicate can be divided into basically three most common techniques:

- Implicit communication "*through the world*" (*i.e.*, *stigmergy*) – robots sense the effects of team-mates' actions through their effects on the world [2] [3] [4] [5];
- Passive action recognition – robots use sensors to directly observe the actions of their teammates [6];
- Explicit (intentional) communication – robots directly and intentionally communicate relevant information through some active means (*e.g.*, *WiFi*) [7] [8].

Within the three techniques described above, the use of explicit communication is the most appealing method because of its directness and ease with which robots can become aware of the actions and/or goals of their teammates. The main uses of explicit communication in multi-robot teams are to synchronize actions, exchange information, and to negotiate between robots. Furthermore, explicit communication is a way of dealing with the hidden state problem, in which limited sensors cannot distinguish between different states of the world that are important for task performance.

However, the development of robot teams for unstructured scenarios, such as rescue missions, require that robots are able to maintain communication among them without the aid of a communication infrastructure. In other words, robots need to be able to deploy and maintain a Mobile Ad hoc Network (*MANET*) in order to explicitly exchange information within multi-hop network paths without unnecessarily restricting the team's range [9].

*MANET*s have attracted much attention in the last years within mobile robotics community. The efficient information shared between agents belonging to a multi-robot system (*MRS*) would allow the coordination and cooperation necessary to fulfill collective tasks such as search and rescue (*SaR*). However, such networks typically consist of a large number of distributed nodes (*i.e.*, robots) that organize themselves into multi-hop wireless networks. Therefore, robots may cooperate and route messages for each other [9], *i.e.*, robots can perform the roles of both hosts and routers.

Usually, within the context of *MRS*, a node corresponds to a robot with embedded processor, low-power radio, and typically battery operated. In order for *MANET*s to be cost efficient, the onboard processing, the wireless communication capabilities and the battery power of each robot are highly limited. Moreover, since robots have mobility nature, the topology of the distributed networks is time varying and the strength of the connection can rapidly change or even completely disappear.

A. Our Preliminary works

It was based on those assumptions that the authors proposed a strategy in [9] to ensure the *MANET* connectivity based on attraction-repulsion mechanisms evaluated on the Robotic Darwinian Particle Swarm Optimization (*RDPSO*) (*cf.*, Section II for a brief explanation about the *RDPSO* algorithm). The problem was stated as having a population of N robots, divided into several swarms of N_S robots, $s \in \mathbb{N}$, wherein each robot would be both an exploring agent of the environment and a mobile node of a *MANET* that performs packet forwarding, according to a paradigm of multi-hop communication. The goal was to ensure that robots would explore an unknown environment, while ensuring that the *MANET* regarding their swarm would remain connected throughout the mission. For that purpose, the connectivity between robots was described by means of a *link matrix* $L = \{l_{ij}\}$ for a N_S-node network, where each entry represents the link between robot i and j. The link was defined as either the *link distance* [10] or the *link quality* [11] (*e.g.*, Received Signal Strength Indicator (*RSSI*)), between pairs of robots. Simulation results showed that the influence inherent to communication's limitations can be attenuated as the number of robots or the communication range/quality increases.

Recently, the authors proposed a natural extension of [9], focusing on a fault-tolerance strategy to guarantee k-connected *MANET*s within each swarm, $k \in \mathbb{N}$ and $k \leq N_S - 1$ [12]. Hence, a given robot would choose its k-nearest neighbors and the virtual force to maintain the *MANET* connectivity was represented by the vector sum of k-virtual forces. A population of 15 physical robots, denoted as *eSwarBots* [13], was used to evaluate such strategy. Experimental results showed that the proposed fault-tolerance *RDPSO* would enable the overcoming of several robot failures such as energy depletion. This work follows the same principles previously addressed in other works such as [14] and [15] regarding the need to maintain a pervasive *MANET*.

Nevertheless, only by securing that each robot may communicate with its teammates does not ensure an efficient group communication. Besides studying the necessary information to be exchanged between teammates, routing protocols should be designed based on the mission-related contextual information, *i.e.*, based on the behavior that one should expect from the *MRS*.

B. Prior works

Bearing in mind such assumptions, many works on *MRS* has been focused on efficiently sharing information between teammates [16, 17, 18]. Rocha [16] addressed the problem of building volumetric maps efficiently sharing the necessary information based on mutual information minimization. To that end, the author presented a distributed architecture model with efficient information sharing, wherein entropy was used to define a formal information-theoretic background to reason about the mapping and exploration process. This allows to share only information that may be relevant for the team. It was with that same principle that Hereford and Siebold [17] proposed a swarm exploration strategy wherein robots only shared their position if their own solution was the best solution in the whole swarm. Although this is an interesting strategy, robots still need to share information concerning their own solution and a global assessment of the collective performance needs to be carried out. Similarly, the authors in [18] proposed a communication-efficient dynamic task scheduling algorithm for *MRS*. This algorithm avoided unnecessary communication by broadcasting global information only to the robots who were interested in it, thus reducing the communication overhead. Simulation experiments showed that the proposed strategy was able to reduce the communication cost to almost half when compared to a common broadcast approach.

Besides exploiting the necessary information that robots should share, routing protocols, such as the well-known Ad hoc On-demand Distance Vector (*AODV*), have been successively extended based on the mobile network requirements [19, 20, 21]. For instance, the authors in [19] extended the *AODV* routing protocol based on the Manhattan mobility model, thus making it more fitted for *Vehicular Ad hoc Network* (*VANET*) applications. Such strategy allowed the establishing of more stable routes, especially in applications demanding a high mobility of nodes, thus reducing the communication overhead of the network. More generally, Asenov and Hnatyshin [20] extended the *AODV* based on the geographical position of nodes retrieved with Global Positioning Systems (*GPS*). This improves the performance of the *route discovery* process in *AODV* routing (*cf.*, Section IV-A for a description about this mechanism). Nevertheless, such strategy assumes that each robot in the network is aware of all teammates' position, thus increasing the communication complexity. Similarly, the work presented in [21] proposed two *GPS*-based strategies, namely the *AODV* Location Aided Routing (*LAR*) protocol and the *AODV Line* protocol, to minimize the control overhead of the *AODV* protocol, thus limiting the flooding area of *AODV*. While the first protocol limits the *route discovery* to a small area of the network, the second protocol uses node location information to restrict route search area to be only near the line connecting source and destination nodes. However, both strategies still present the same disadvantage as the work in [20], *i.e.*, the knowledge about the current position of all robots.

C. Statement of contributions and paper outline

Although this work revolves around the *RDPSO* first presented in [22] and briefly described in Section II, the same analysis may be conducted to other behavior-based architectures. The main contributions of this work are as follow:

i) The data exchanged between robots of the same swarm, *i.e.*, network, is studied in depth and a rationale is presented for each different situation within the *RDPSO* context so as to minimize the communication overhead (Section III);
ii) The traditional *AODV* reactive routing protocol is extended based on the *RDPSO* dynamics to minimize the number of updates regarding the routes connecting pairs of robots, thus avoiding unnecessary flooding (Section IV);
iii) Based on the proposed approaches, the communication complexity of the *RDPSO* is evaluated using both physical and virtual robots in a large indoor environment (Section V).

Sections VI and VII outline the discussion and main conclusions, respectively.

II. ROBOTIC DARWINIAN PSO

This section briefly presents the *RDPSO* algorithm proposed in [22]. The Darwinian *PSO* (*DPSO*) was originally presented by Tillett *et al.* [23] for optimization problems, being an evolutionary algorithm that extends the well-known *PSO* [24] using natural selection, or survival-of-the-fittest, to enhance the ability to escape from sub-optimal solutions. The *RDPSO* is an extension of the *DPSO* to multi-robot applications presented for the first time in [22] and further improved in several subsequent publications such as [25] and [26], thus presenting the following features:

- *Social Exclusion and Inclusion* - The *RDPSO* is represented by *multiple swarms* (*i.e.*, group of robots from the same network) wherein each swarm individually performs just like a *PSO*-like robotic algorithm in search for the solution and some rules govern the whole population of robots. The socially excluded robots randomly wander in the scenario instead of searching for the objective function's global optimum like the other robots in the active swarms do. However, they are always aware of their individual solution and the global solution of the socially excluded group.
- *Obstacle Avoidance* - A new cost or fitness function is defined in such a way that it guides the robot in performing the main mission while avoiding obstacles. For this purpose it is assumed that each robot is equipped with sensors capable of sensing the environment for obstacle detection within a finite sensing radius r_s. A monotonic and positive *sensing function* $g(x_n[t])$ at each discrete time, or iteration, $t \in \mathbb{N}$, is defined. This function depends on the sensing information, *i.e.*, distance from the robot to an obstacle.
- *Ensuring MANET k-Connectivity* - Robots' position needs to be controlled in order to maintain the communication based on constraints such as maximum distance or minimum signal quality. The way to preserve the network connectivity depends on the characteristics of the communication. Assuming that the network supports multi-hop connectivity, the communication between two end nodes (*i.e.*, robots) is carried out through a number of intermediate nodes whose function is to relay information from one point to another. Considering that nodes are mobile, it is necessary to guarantee the communication between all nodes. The robots' position is updated by means of the ensuring *MANET* connectivity algorithm first presented in [9] and further extended in [12] to consider k-fault-tolerance, *i.e.*, each pair of robots from the same swarm is connected to, at least, k robot-disjoint paths.

The behavior of robot n can be described by the following discrete equations at each discrete time, or iteration, $t \in \mathbb{N}_0$:

$$v_n[t+1] = w_n[t] + \sum_{i=1}^{4} \rho_i r_i (\chi_i[t] - x_n[t]), \tag{1}$$

$$x_n[t+1] = x_n[t] + v_n[t+1], \tag{2}$$

wherein coefficients ρ_i, $i = 1,2,3,4$, assign weights to the local best (*i.e.*, cognitive component), the global best (*i.e.*, social component), the obstacle avoidance component and the network connectedness enforcement component when determining the new velocity, with $\rho_i > 0$. Parameters r_i are random vectors wherein each component is generally a uniform random number between 0 and 1. $v_n[t]$ and $x_n[t]$ represents the velocity and position vector of robot n, respectively. $\chi_i[t]$ represent the best position of the cognitive, social, obstacle and *MANET* components. The cognitive $\chi_1[t]$ and social components $\chi_2[t]$ are the commonly presented in the classical *PSO* algorithm. $\chi_1[t]$ represents the local best position of robot n while $\chi_2[t]$ represents the global best position of robot n. The other features $\chi_3[t]$ and $\chi_4[t]$ are novel and inherent to multi-robot applications. In brief, $\chi_3[t]$ represents the local best position of robot n regarding to the sensed obstacles so far. Similarly, $\chi_4[t]$ represents the local best position of robot n that allows maintaining a connected *MANET* based on its closest neighbor, *i.e.*, one-hop robot.

In the common *PSO* algorithm, the inertial component $w_n[t]$ is usually proportional to the inertial influence. The *RDPSO* uses fractional calculus (*FC*) [27] [28], to describe the dynamic phenomenon of a robot's trajectory. As presented on [25], the inertial component $w_n[t]$ may be defined as:

$$w_n[t] = \alpha v_n[t] + \frac{1}{2}\alpha v_n[t-1] + \frac{1}{6}\alpha(1-\alpha)v_n[t-2] + \frac{1}{24}\alpha(1-\alpha)(2-\alpha)v_n[t-3], \tag{3}$$

for the *eSwarBot* platforms [13], where α represents the fractional coefficient.

Considering equations (1-3), it is noteworthy that robots will tend to converge to the optimal solution. However, although all robots within a swarm agree with the best solution, they must also fulfill the other requirements (*i.e.*, avoid obstacles and maintain a certain distance between neighbors). In other words, robots within the same swarm do not physically converge to a given solution but instead reach a global consensus. Such consensus is related to the nature of the mission. For instance, if we have a group of mobile olfactory robots that are trying to find a gas leak in an indoor environment (*c.f.*, [29] [30]), each robot's state comprises its pose and the corresponding value of gas density. The swarm will reach a consensus every time the highest gas density is shared among teammates, thus affecting their local decision-making. To avoid swarms' stagnation, the *RDPSO* encompasses the rules presented in Table 1, which are based on the principles of social exclusion and inclusion.

Table 1. Punish-Reward *RDPSO* rules.

PUNISH	***REWARD***
If a swarm does not improve during a specific threshold the swarm is punished by excluding the worst performing robot	If a swarm improves and its current number of robots is inferior to the maximum number of accepted robots to form a swarm, then it has a small probability of being rewarded with the best performing robot that was previously excluded
If the number of robots in a swarm falls below the minimum number of accepted robots to form a swarm, the swarm is punished by being dismantled	If a swarm has been more often rewarded than punished it has a small probability of spawning a new swarm

Nevertheless, to achieve a global consensus within each swarm, robots need to share a certain amount of information as described in the following section.

III. Sharing Information Within the RDPSO

It has generally been assumed in *MRS* that each robot has the ability to communicate with any other robot with small consideration for the quality and performance of the wireless communication network. Although being valid in particular situations, such an assumption does not generally hold. As previously described, the *RDPSO* ensures the connectivity of the network (*cf.*, $\chi_4[t]$ term in previous section and [12] for a more detailed description). Nevertheless, how this is carried out in practice without overloading the communication channel needs to be addressed. Moreover, the communication packet structure shared between robots needs to be specified and a rational behind it should be introduced. Generally, the packet data structure may be illustrated as presented in Fig. 1.

Header bit [0,1]		Data byte(s)
0	Local Broadcast to neighbors	Number of bytes depends on specific data
1	Broadcast to whole swarm	

Fig. 1. General communication packet structure for a swarm of N_s robots.

It is noteworthy that the broadcast to the whole swarm should be avoided as it represents a high communication complexity. In brief, in order to broadcast to the whole swarm by multi-hop communication, the message needs to be addressed to each Robot *ID*. The number of bytes necessary for the main message, *i.e.*, Data byte(s), will depend on the message itself. For instance, if a robot wants to share its position and considering a planar scenario, then two bytes may be enough to represent the coordinate on each axis.

D. Ensuring Connectivity

Since robots may move apart to further areas, it is important to have a pervasive networking environment for communications among robots. Furthermore, without a preexistent infrastructure, robots need to be able to act as intermediate nodes, *i.e.*, routers, in order to relay information from one point to another, thus supporting multi-hop communication in a *MANET* [31].

In a previous work, an initial deployment strategy denoted as *Extended Spiral of Theodorus* (*EST*) was presented [12]. The *EST* was introduced as an autonomous, realistic and fault-tolerant initial deployment strategy based on the Received Signal Strength Indicator (*RSSI*) signal. Similarly to Rybsky's work [32], the initial deployment of robots was carried out hierarchically dividing the population of robots into *rangers* and *scouts*. Each *ranger* handled the initial deployment of an entire swarm of *scouts* allowing a distributed and autonomous transportation, thus sparing the need of a preprocessing procedure (*e.g.*, topological features extraction using unmanned aerial vehicles). In other words, the initial deployment was able to ensure that each exploring robot would be able to communicate with k neighbors from the same swarm, $k \in \mathbb{N}$, thus ensuring that the *MANET* is k-connected.

After the initial deployment process is concluded, robots explore the environment while ensuring the same k-connectivity of the swarm by defining $\chi_4[t]$ as a set of attractive and repulsive forces [12]. Let us consider the following illustrative example presented in Fig. 2 in which it is necessary to guarantee a biconnected network ($k = 2$). As it is possible to observe, robot 1 chooses robot 2 and 4 as its nearest neighbors since they are the nearest ones or the ones that present the higher signal quality. As the link between robot 1 and 2 corresponds to the ideal situation such that any attractive or repulsive force is necessary. However, robot 4 is too far away from robot 1, thus resulting in an attraction virtual force toward it. Robot 2 chooses robot 3 and robot 4 as its nearest neighbors since robot 1 has first chosen robot 2. As robot 3 is too close from robot 2, a repulsive force is generated. On the other hand, as robot 4 is too far away from robot 2, an attractive force is generated. The resulting force will then allow robot 2 to move away from robot 3 while getting closer to robot 4. Finally, the two nearest neighbors of robot 3, that did not chosen it as their nearest neighbor, are robot 1 and robot 4 which are too far away, thus being affected by attractive forces toward them.

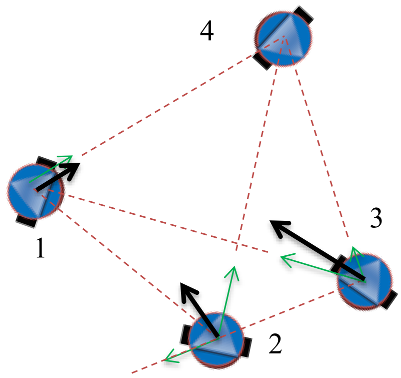


Fig. 2. Illustration of a *MANET* topology of a swarm. Dashed lines represent the link quality between pairs of robots, thinner arrows represent the force vectors regarding each chosen neighbor and larger arrows represent the resulting force vectors that ensure *MANET* biconnectivity.

Based on the presented strategy, it is possible to ensure the k-connectivity of the network by simply sharing the position to the k neighbors. Therefore, only taking into consideration the information of the N_b robots within the one-hop path (*i.e.*, neighbors) would allow ensuring the connectivity of the whole swarm. Fig. 3 presents the packet structure of communication for this particular situation.

Header bit	Data byte(s)
0	$x_n[t]$

Fig. 3. Communication packet structure that allows robots in maintaining the *MANET* k-connectivity within their swarm of N_s robots.

An alternative to broadcasting the position to the N_b neighbors would be the use of strategies to find the teammates position under their visual range [33]. For instance, if robots are equipped with laser range finders, retro-reflective markers may be used for recognition. To that end, one should ensure that the sensing radius r_s is equal or superior to the maximum distance of neighbors, which depends on the minimum inter-robot signal quality *RSSI*.

E. Converging to the Optimal Solution

As previously presented in section II, $\chi_2[t]$ represents the best positions of the social component. Therefore, robots from the same active swarm, *i.e.*, not in the socially excluded group, need to share their best cognitive solution $f_n[t]$ and current position $x_n[t]$ so as to compute the position of the robot that has the best social solution. For instance, if one wishes to find a gas leak, the best performing robot will be the one with the highest solution, *i.e.*, $\max_{n \in N_s} f_n[t]$. Nevertheless, efficiently sharing this information may allow to drastically reduce the communication complexity of the *RDPSO*. For instance, if a robot from the active swarm was unable to improve, then the information about its position and solution are irrelevant to the group, *i.e.*, the collective behavior will not change. Therefore, and as a rule, a robot may only share its current solution and position if it is able to improve its best cognitive solution, *i.e.*, $f_n[t+j] > f_n[t], j \in \mathbb{N}$. Otherwise, and as robots are able to memorize the best solution of the swarm and corresponding position so far, without significantly increase the memory complexity, robots will simply continue computing their algorithm without communicating. Fig. 4 represents the packet structure sent from a robot that was able to improve its solution.

Header bit	Data byte(s)	
1	$x_n[t]$	$f_n[t]$

Fig. 4. Communication packet structure that allows robots from active swarms to cooperatively converge to the solution. This packet is only sent if a robot improves its best cognitive solution.

Note that this significantly reduces the communication complexity as this data needs to be exchanged between all teammates, *i.e.*, broadcasted to the whole swarm by means of multi-hop communication. For instance, in a previous work [34], a setup of 4, 8 and 12 *educative Swarm Robots* (*eSwarBots*) [13] on a small scenario with one optimal and one sub-optimal solution was presented (Fig. 5a). As Fig. 5b depicts, using 12 robots represent the most critical situation tested regarding the chances that the swarm has to improve. Even so, in a population of 12 robots under the 80 trials of 180 seconds each, it was possible to observe that a robot is only able to improve in approximately 15% of the iterations, *i.e.*, only approximately 15% of the information shared is useful to the collective performance. As the number of robot decreases for the same scenario, the probability that a robot has to improve also slightly decreases, thus slightly decreasing the amount of useful information (Fig. 5b).

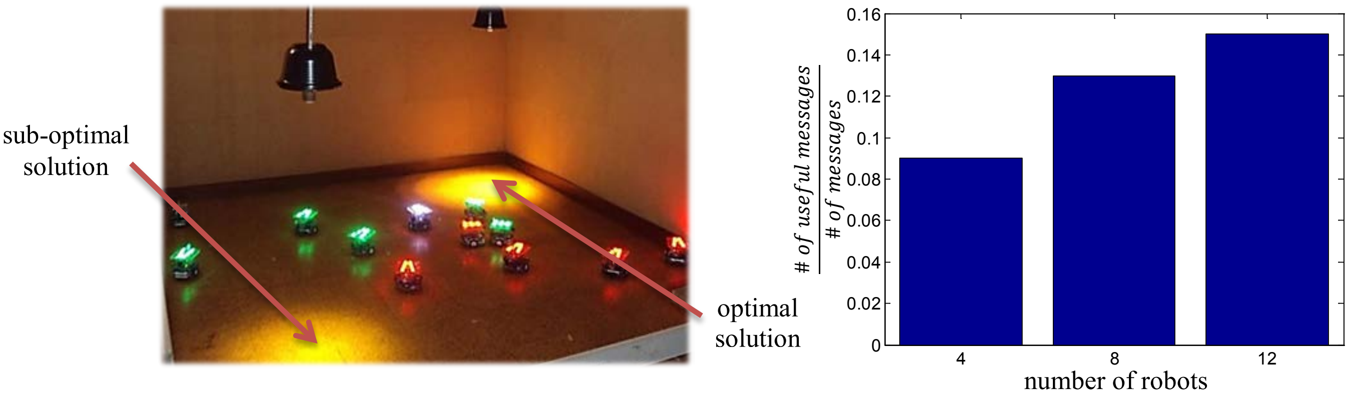


Fig. 5. a) Experimental setup presented in [34]; b) ratio between the number of useful messages and the total number of messages.

It is noteworthy that the amount of useful information will vary depending on several conditions (*e.g.*, number of robots, scenario, mission objectives, among others). Nevertheless, efficiently sharing information based on the herein proposed strategy will always significantly reduce the communication complexity of the algorithm as robots will not always improve at each iteration. After this analysis on the data exchanged between robots from active swarms, next section shows an efficient way to share information between excluded robots, *i.e.*, robots within the socially excluded group.

F. Avoiding Sub-Optimality

As previously presented in section II, the way the *RDPSO* handles sub-optimal avoidance is by socially excluding robots that have nothing to offer to the group, *i.e.*, that are unable to improve for a certain stagnancy threshold (*cf.*, [22] and Table 1 for a more detailed description about this "punish"-"reward" mechanism). In brief, the number of times a swarm evolves without finding an improved objective is tracked with a search counter. If a swarm's search counter exceeds a maximum critical threshold, the swarm is punished by excluding the worst performing robot, which is added to a socially excluded group. Nevertheless, the behaviour of those socially excluded robots differs from the ones in the active swarms. Instead of searching for the optimal solution (*i.e.*, the main activity of the society) like the other robots in the active swarms do, they randomly wander in the scenario while avoiding obstacles and maintaining the *MANET* connectivity with the other excluded robots. Note, however, that they are always aware of their best cognitive solution. That being said, the only regular information excluded robots need to share is their current position to their neighbors so as to maintain the *MANET* connectivity (*cf.*, Section III-A).

However, if an active swarm continues to improve for a certain amount of time, there will be a probability to be rewarded with the best performing robot from the socially excluded group. Moreover, the swarm will also have a small probability of creating a new swarm from the best performing robots from the socially excluded group. Therefore, when excluded robots receive a calling from an active swarm, they will broadcast their best cognitive solutions and respective positions to the whole socially excluded group by means of multi-hop communication (*cf.*, Section III-B). Thereby, they will be able to assess the best performing excluded robots so far and evaluate which ones would be a part of an active swarm.

Although one wishes to avoid broadcasting to the whole multi-hop network, this event will only occur from time to time since it depends on the constant improvement of swarms and a probability of successful calling. Furthermore, an adequate choice on the routing protocol may allow overcoming or, at least, minimizing the broadcast overhead.

IV. Routing Protocol

In *MANET*s, the communication between source and destination nodes may require traversal of multiple hops. Since the introduction of such networks, a community of researchers has proposed a variety of routing algorithms, mainly divided into two classes: *i*) proactive; and *ii*) reactive. In the first class, every node maintains a list of destinations and their routes by processing periodic topology broadcasts originated by each node in the network. In reactive routing protocols, nodes maintain their routing tables on a need-to-use basis. For more information about those two classes please refer to [35].

Although many works has been comparing such routing protocols (*e.g.*, [36], [37], [38]), those have been mostly carried out in simulation and outside the scope of swarm robotic applications, wherein a large quantity of highly dynamic nodes need to be considered. Within such assumptions, the class of proactive routing protocols utterly falls apart. Besides being unsuitable to use in highly mobile nodes, proactive routing requires a high communication cost to constantly maintain all topological information.

Therefore, and as swarm robotics aims for scalability under an increasing numbers of robots and mobility rate within the network, this work will focus on reactive routing protocols. One of the most well-known reactive protocols is the Ad hoc On-demand Distance Vector (*AODV*).

A. Ad hoc On-demand Distance Vector (AODV)

The *AODV* routing protocol is one of the most adopted reactive *MANET* routing protocols [39]. This protocol exhibits a good performance on *MANET*s, thus accomplishing its goal of eliminating source routing overhead. Nevertheless, at considerably high rates of node mobility, it requires the transmission of many routing overhead packets. Despite this limitation, the *AODV* has been extensively applied in most wireless equipment, such as the one used on the robotic platforms *eSwarBots* [13] (Fig. 6a); the Original Equipment Manufacturers *RF* (*OEM-RF*) *XBee* Series 2 from *Digi International* [40] (Fig. 6b).

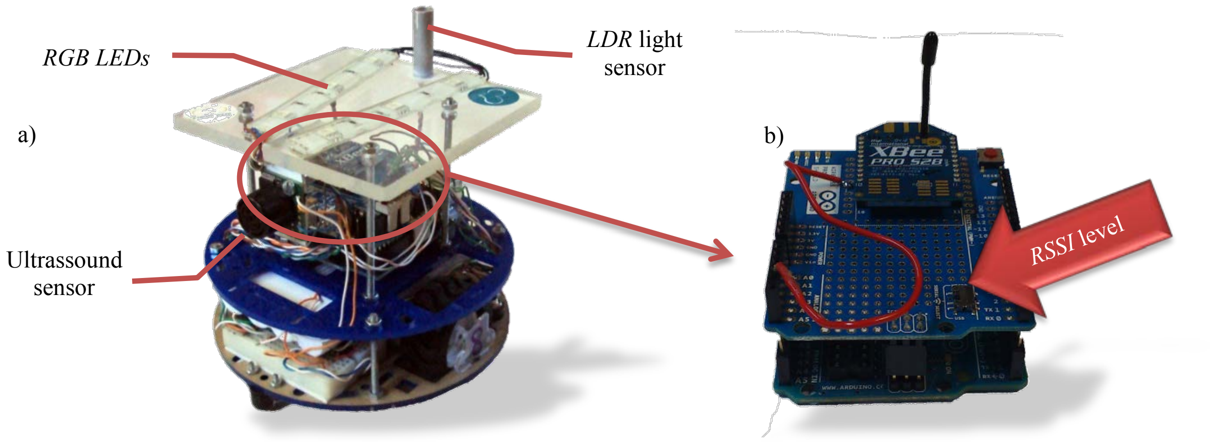


Fig. 6. a) *eSwarBot* platforms presented in [13]; b) Electrical modification of *XBee Series 2* from *Digi International* [40] to provide the *RSSI* signal output.

Under the *AODV* protocol, when a robot A needs to communicate to robot B, it broadcasts a *route discovery* message to its neighbors (*i.e.*, local broadcast), including the last known sequence number for that destination [41]. The *route discovery* is flooded through the network until it reaches a robot that has a route to the destination. Each robot that forwards the *route discovery* creates a reverse route for itself back to robot A. When the *route discovery* reaches a robot with a route to robot B, that robot generates a *route reply* that contains the number of hops necessary to reach robot B and the sequence number for robot B most recently seen by the robot generating the *route reply*. Each robot that participates in forwarding this *route reply* back toward robot A creates a forward route to robot B. Hence, each robot remembers only the next hop and not the entire route.

In order to maintain routes, *AODV* normally requires that each robot periodically transmit a *hello message*. Within the *RDPSO* algorithm, this may be accomplished at each step of the algorithm, *i.e.*, after reaching a desired position $x_n[t+1]$, thus benefiting from the need to share its current position in order to ensure *MANET* connectivity (Section III-A). A previously defined link may considered to be broken if a robot does not receive three consecutive *hello messages* from a neighbor. Under that condition, any upstream robot that has recently forwarded packets to a destination using that link is notified via an *unsolicited route reply* containing an infinite metric for that destination. Upon receipt of such a *route reply*, a robot must acquire a new route to the destination using the *route discovery* once again.

B. RDPSO based AODV

Although the mechanics of the *AODV* are quite transparent for users in most wireless technology (*e.g.*, *OEM-RF XBee* Series 2), one may need to extend the original *AODV* features so as to further adapt it to the application itself (*e.g.*, [19]). In this work, the *AODV* is extended based on two key elements: *i*) as the teams of robots begin connected by mean of the *EST* initial deployment (*cf.*, [12]), a *node discovery* functionality was introduced; and *ii*) the mobility of robots within the *RDPSO* behavior is taken into account so as to establish more stable routes.

The *node discovery* basically allows discovering the *ID*s of all robots that have joined the network. Each robot will then broadcast a *node discovery* command throughout the network. All robots that receive the command will send a response that includes its own address. A timeout is defined by the *node discovery* sender, thus allowing specifying an amount of time a robot will spend in discovering its teammates. In other words, the *node discovery* functionality is highly suitable as the *RDPSO* handles multiple swarms and it may be difficult to predefine a population of specific robots to form a swarm in advance. Moreover, such strategy avoids the need to configure the address of each robot independently as each robot will acquire the default *ID* of its teammates in the beginning of the mission. Therefore, after each swarm is deployed within the scenario, the very first action robots must perform is the *node discovery* command. Afterwards, the *route discovery* will be carried out (*cf.*, previous section) and the mission will start.

Subsequently, it is possible to improve the *AODV* based on the mobility of robots, by first understanding how robots may generally behave within the *RDPSO* algorithm. As previously presented in Section II, the *RDPSO* model depends on the sensed information (1), both cognitive and social, and the inertial coefficient based on the approximate fractional difference of order α (3). That being said, a robot may estimate where a neighbor, *i.e.*, one-hop robot, will be in the next iteration by knowing its previous positions, its best position so far and the social solution of the group.

The later situation is the simplest one as each robot is always aware of the best solution of the whole group so far (Section III-B). Hence, this requirement does not increase the memory complexity of the algorithm at all.

Similarly, a robot may know the best position of its neighbors as it is intrinsic to the communication packet structure shared when robots improve their individual solution (Section III-B). For this situation, each robot will need to keep the position received by robots when they are able to improve *i.e.*, $f_n[t+j] > f_n[t], j \in \mathbb{N}$. Nevertheless, the position of non-neighbor robots may be discarded as this is a distributed strategy that only considers information from one hop nodes. Therefore, this results in an addition of the memory complexity per robot equal to the number of neighbor robots, *i.e.*, $\mathcal{O}(N_b)$. Note, however, that this only represents memorizing twice N_b bytes necessary to represent the planar best position of each neighbor robot.

The most memory demanding situation will be inevitably memorizing the position of neighbors over time. Based on equation 3, one may compute the motion of robots with the information of the four last steps, *i.e.*, $v_n[t-j], j = 0, \ldots, 3$. As neighbor robots share their current position $x_b[t]$, $b \in N_b$, a robot needs to memorize the two consecutive positions $x_b[t]$ and $x_b[t-1]$ of all its neighbors so as to calculate their current velocity $v_b[t]$ (*cf.*, equation 2). In other words, a robot will need to keep track the position of all its N_b neighbor robots for the last 5 steps to estimate their position, *i.e.*, $\mathcal{O}(5N_b)$.

In sum, to extend the *AODV* based on the *RDPSO* behavior, one needs to increase the memory complexity of robots by $\mathcal{O}(6N_b)$. Note that this is a small increment to the memory complexity of each robot when compared to the benefit that this novel mechanism may provide in reducing the communication complexity of the whole swarm.

Having the information described above, each robot may be able to estimate all neighbors' next position $x_b[t+1]$ by means of equation 1, 2 and 3. Nevertheless, as the *RDPSO* is endowed with a stochastic effect, *i.e.*, r_i, $i = 1,2,3,4$, it is almost impossible for a robot to estimate the neighbors' exact next position accurately. However, one may improve the precision of such estimate by considering the expected value of the uniform random parameters. In other words, for the position estimate of the neighbors, a deterministic simplified version of the *RDPSO* is considered. The deterministic simplified *RDPSO* is obtained by setting the random numbers to their expected values:

$$E(r_i) = \tfrac{1}{2}, i = 1,2. \tag{4}$$

Thus, for the deterministic simplified *RDPSO*, replacing the random factors r_i by $\frac{1}{2}$, equations 1, 2 and 3 may be rewritten in a single equation as:

$$\begin{aligned} x_{n,b}^e[t+1] = &\left(-1 - \alpha + \tfrac{1}{2}\textstyle\sum_{i=1}^{4} \rho_i\right) x_{n,b}[t] + \left(\tfrac{1}{2}\alpha\right) x_{n,b}[t-1] + \left(\tfrac{1}{3}\alpha + \tfrac{1}{6}\alpha^2\right) x_{n,b}[t-2] + \\ &\left(-\tfrac{1}{24}\alpha^3 - \tfrac{1}{24}\alpha^2 + \tfrac{1}{12}\alpha\right) x_{n,b}[t-3] + \left(\tfrac{1}{24}\alpha^3 - \tfrac{1}{8}\alpha^2 + \tfrac{1}{12}\alpha\right) x_{n,b}[t-4] + \tfrac{1}{2}\rho_1 \chi_{1_{n,b}}[t] + \tfrac{1}{2}\rho_2 \chi_{2_{n,b}}[t], \end{aligned} \tag{5}$$

in such a way that $x_{n,b}^e[t+1]$ represents the position of robot b estimated by its neighbor n. Note that the remaining parameters in equation 5 are explained on section II. Although the estimated position is unlikely to be exactly the same as the real position, *i.e.*, $x_{n,b}^e[t+1] \neq x_b[t+1]$, a good approximation may be enough to select if robot b may be a candidate to be the intermediate in route between source and destination robots.

Therefore, to improve the *AODV* routing protocol, when a source robot wants to send a packet to a destination robot, it will first estimate the next position of neighbor robots. Then, it will recognize the intermediate robot that can participate in the routing of the message. The robot can be selected as the next hop if its estimated position is the closest to the destination robot, *i.e.*, the one with the smallest Euclidean distance.

$$ID_b = \text{argmin}_{b \in N_b} d\left(x_{n,b}^e[t+1], x_f^e[t+1]\right), \tag{6}$$

wherein ID_b will represent the *ID* of robot n's neighbors that has the smallest distance to the destination robot and $x_f^e[t+1]$ the estimated position of the destination robot. After the message reaches the selected robot, the same process is carried out in order to assess the neighbor robot that would yield the next most fitted hop. Hence, source robot, destination robot and candidate robot for next hop are the inputs of the herein proposed strategy for each robot. It is noteworthy that the information that will be used from the destination robot will be the last known information obtained from the broadcast to the whole swarm (*cf.*, Section III-B). Although the destination robot is likely to have changed is position in the meanwhile, the idea is to have an estimate on the region where to send the message to and choose the most adequate path.

Routes established within such strategy are more stable and have less overhead than the original *AODV* routing method. Nevertheless, this is a greedy distributed strategy and it may happen that a robot cannot find any intermediate node as next best hop. For instance, the source robot may choose the incorrect neighbor robot based on its location without knowing that it may not have any other neighbors at all besides itself. In this situation, *i.e.*, when a message returns to a robot that already forwarded it or to the source robot, then the common *AODV* mechanism of *route discovery* is used between that robot and the destination one (*cf.*, Section IV-A).

To easily understand the herein proposed strategy, Fig. 7 presents an illustrative example of a swarm under the *RDPSO* algorithm. In the beginning (Fig. 7a), and due to *RDPSO* main mechanisms [12], robots are able to communicate between themselves, thus guaranteeing the *MANET* connectivity. Since the *AODV* routing protocol is the one adopted in this work, its main mechanism to retrieve all routes between robots is fulfilled, *i.e.*, *route discovery*, as presented in Section IV-A. The routes between robots are represented by the blue thin lines that connect them. Due to the particularities of the *RDPSO*, the *node discovery* is carried out so as to retrieve the *ID*s of all robots within the same swarm. While any robot improves, they will continue exploring the scenario informing its neighbors about its position to maintain the *MANET* connectivity (Section III-A). After a while (Fig. 7b), robot 2 is able to improve its cognitive solution, thus informing all other robots within the swarm (Section III-B). Since robot 2 cannot communicate with robot 6, and considering the traditional *AODV*, a new route needs to be found, *i.e.*, the route discovery needs to be fulfilled once again. Those new routes are represented by the red thick lines that connect the robots. Nevertheless, the *route discovery* mechanism requires successive local broadcasts that may overload the communication channel. Fig. 7c depicts the mechanism inherent to the *RDPSO* based *AODV*. Within such strategy, robot 2 will choose the nearest neighbor that presents the smallest distance to robot 6 (*cf.*, equation 6). As robot 2 is able to directly communicate to robot 6, it will forward the message to it.

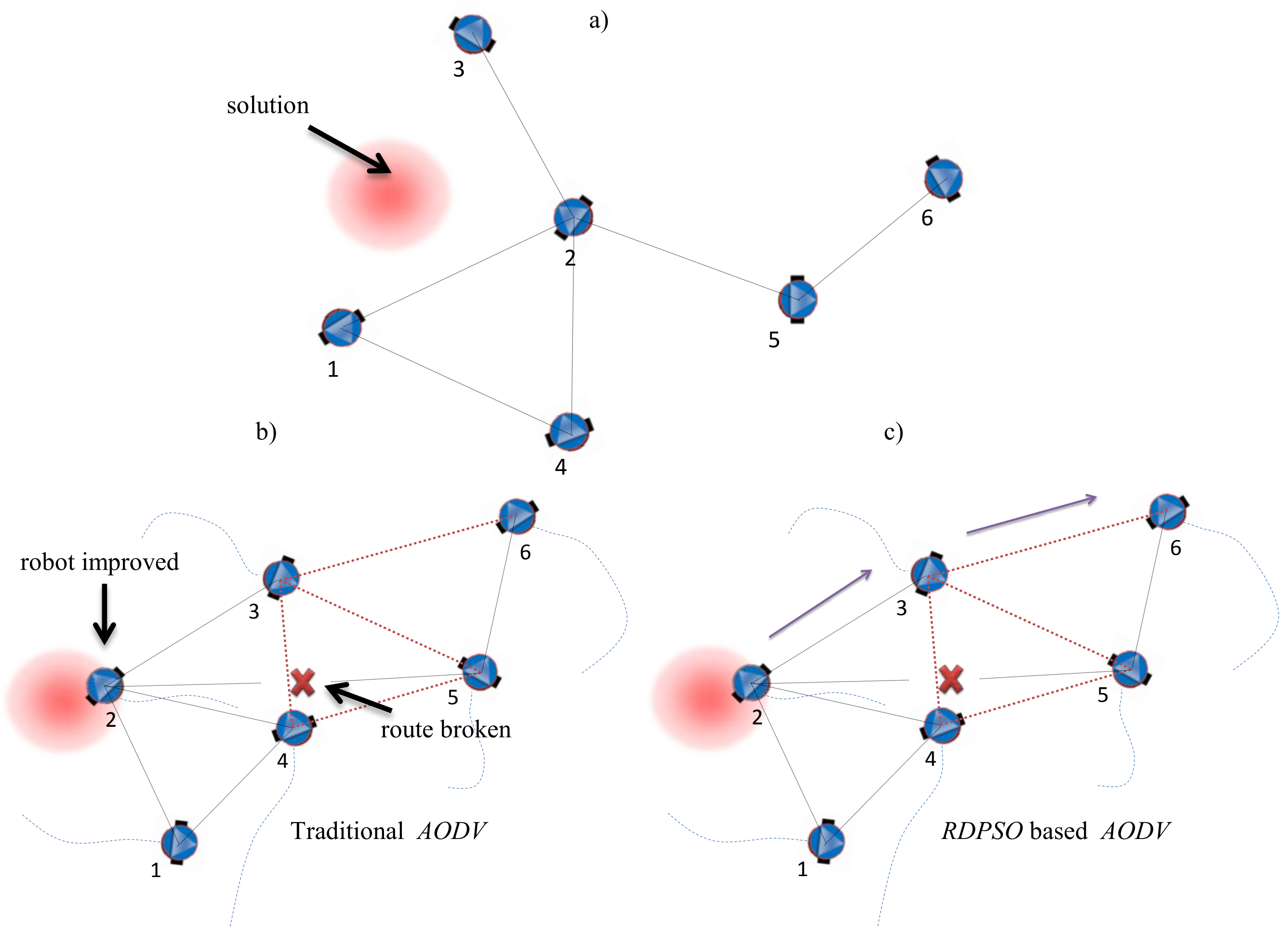


Fig. 7. *RDPSO* based *AODV* routing protocol. Red bolder lines between robots represent that there exists a possible link between them but that the *AODV* protocol is unaware of. a) The robots start connected by means of the *EST* initial deployment strategy, thus enforcing the *MANET* connectivity of the whole swarm [12]. The node discovery and route discovery allows to retrieve the *ID* of all robots and build the routes between them (blue thin lines). b) After a while, robot 2 improves and tries to broadcast its new solution and position to the whole network. However, as robot 2 is unable to communicate with robot 6 by means of the route previously built using *AODV*, a new route discovery needs to be sent (red thick lines). c) Using the *RDPSO* based *AODV* will allow robot 2 to choose the neighbor that is near robot 6, *i.e.*, robot 3, that will forward the message to its destination, *i.e.*, robot 6.

The whole *RDPSO* communication procedure for a robot n may be briefly summarized as presented by Algorithm I. Note that Algorithm I only focus on the shared information between robots and the routing protocol. For a detailed description of the *RDPSO* main behavior please refer to [42].

Algorithm 1. Sharing information within the *RDPSO*

```
starting( ) // wait for information about initial position x_n[0] and swarmID
fullIDs = node_discovery(swarmID) // full list of robot IDs from the same swarm swarmID
routesIDs = route_discovery(fullIDs) // list of routes within the same swarm swarmID
Main_Loop
  If swarmID ≠ 0 // it is not an excluded robot
    send(0, x_n[t]) // local broadcast may be avoided applying recognition techniques in visual range (Section III-A)
    f_n[t] = sense( ) // evaluate individual solution f_n[t]
    If robot_improved(f_n[t − 1], f_n[t]) // robot n will globally broadcast its current solution and position (Section III-A)
      listIDs = send(1, x_n[t], f_n[t]) // listIDs is an array of robot IDs that did not received the message
      resend(listIDs) // use the RDPSO based AODV
      If call_robot( ) // robot n may call a new robot from the excluded group to its swarm
        send(0, swarmID_call) // broadcast the possibility to receive a new robot
      If create_swarm( ) // robot n may create a new swarm from the excluded group
        send(0, swarmID_new) // broadcast the possibility to create a new swarm
    If received_fwdmsg(ID_f, x_n[t], f_n[t], routesIDs) // ID_f represents the ID of the destination robot
      resend(ID_f) // use the RDPSO based AODV
  Else // it is an excluded robot
    wander( ) // Section III-C
    send(0, x_n[t]) // local broadcast may be avoided applying recognition techniques in visual range (Section III-A)
    f_n[t] = sense( ) // evaluate individual solution f_n[t]
    If received(swarmID_call) Or received(swarmID_new) // call for a new robot or swarm received
      listIDs = send(1, x_n[t], f_n[t]) // listIDs is an array of robot IDs that did not received the message
      resend(listIDs) // use the RDPSO based AODV
End // until stopping criteria (e.g., convergence, time)
resend(listIDs) // RDPSO based AODV function
  For i = 1 to len(listIDs) // check unreached robots one by one from listIDs
    For j = 1 to N_b // estimate position of its N_b neighbors (equation 5)
      b = fullIDs(j)
      x^e_{n,b}[t + 1] = estimate_pos(x_{n,b}[t], …, x_{n,b}[t − 4], χ_{1,2 n,b}[t])
    ID_b = min_{b∈N_b} d(x^e_{n,b}[t + 1], x^e_{listIDs(i)}[t + 1]) // find closest neighbor to robot listIDs(i) (equation 6)
    If ID_b = listIDs(i) // the unreached robot listIDs(i) is a neighbor
      send(ID_b, x_n[t], f_n[t]) // send message directly to robot ID_b
    Else
      If find(ID_b, routesIDs) // the robot ID_b already exists in the route necessary to reach listIDs(i)
        routesIDs = route_discovery(fullIDs) // necessary as it is unable to reach the destination robot
        send(listIDs(i), x_n[t], f_n[t]) // send message to robot listIDs(i)
      Else
        routesIDs = update_route(n, ID_b, listIDs(i)) // update the route necessary to reach listIDs(i)
        send(ID_b[listIDs(i)], x_n[t], f_n[t], routesIDs) // send message to robot ID_b so as to reach listIDs(i)
End
```

Next section evaluates the communication complexity of the *RDPSO* with and without the herein proposed strategies.

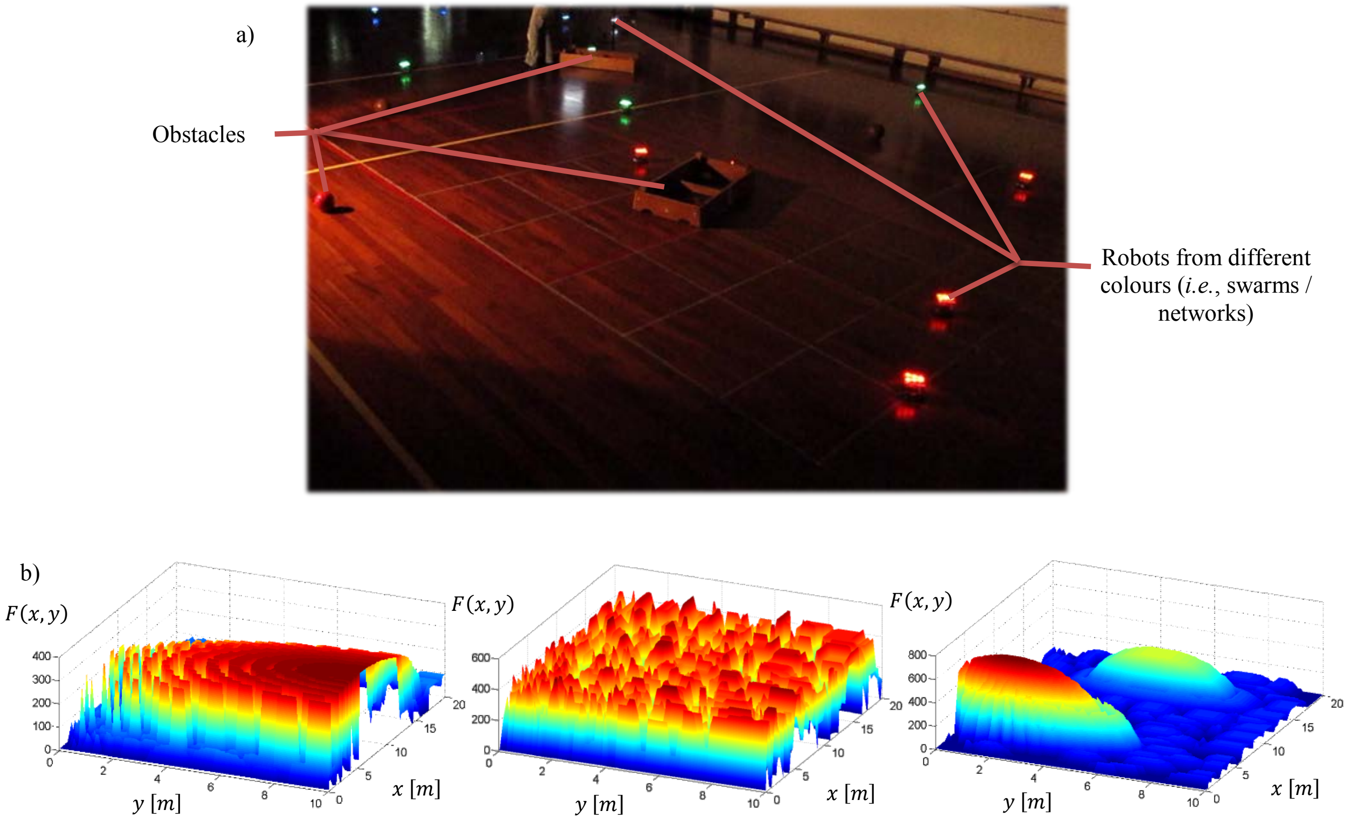
V. Experimental Results

This section is divided into three sub-sections exploring and comparing the properties of the “regular” version of the *RDPSO* (previously presented) to its counterpart version proposed in this paper – the “optimized” *RDPSO*.

A. Real-World Experiments

In this section, it is explored the effectiveness of the proposed communication methodology on a group of 15 *eSwarBots* [13], *i.e.*, $N = 15$, performing a distributed exploration task under the *RDPSO* behavior (Fig. 8). As this paper emphases on the analysis the communication complexity of the *RDPSO*, the convergence of the algorithm itself was neglected. This may only be considered as the herein proposed communication methodology does not affect the decision-making of robots since the same useful information is always shared between teammates. Therefore, as *eSwarBots* are equipped with *LDR* light sensors that allow sensing the brightness of light, their solution was affected by the current room lighting conditions, either natural or not. Just for the purpose of illustrating the variability of light over time, Fig. 8b represents the intensity values of light

$F(x, y)$ over a day. Such data was obtained sweeping the whole scenario with a single robot with the light sensor connected to a 10-bit analog input resulting in a resolution of approximately 5 mV.



≈ 8 a.m. (room lights on) ≈ 1 p.m. (lights off) ≈ 6 p.m. ("solution" lights on and room lights off) [5]

Fig. 8. Experimental Setup. a) Arena with 3 swarms (different colors) of 5 *eSwarBots* each; b) Virtual representation of the target distribution over day with under different lighting conditions.

Since the *RDPSO* is a stochastic algorithm, it may lead to a different trajectory convergence whenever it is executed, thus resulting in a different amount of information exchanged between robots. Therefore, two sets of 20 trials of 360 seconds each were considered. In other words, the "regular" *RDPSO* (first set of trials) was compared with the "optimized" *RDPSO* (second set of trials), *i.e.*, the extension of the *RDPSO* based on the strategies presented in Section III and IV. At each trial, the robots were deployed in a 20×10 meters indoor scenario (Fig. 8a) ensuring the initial connectivity of each swarm in a spiral manner (*cf.*, Section II or [12] for a more detailed description).

The inter-robot communication was carried out using *ZigBee* 802.15.4 wireless protocol. Although the *XBee Series 2* modules allow a maximum communication range of approximately 30 meters in indoor/urban environments (*cf.*, [13]), the signal quality of the received data is highly susceptible to obstacles and other phenomena (*e.g.*, communication reflection and refraction), thus resulting in the loss of packets as the inter-robot distance increases. In fact, preliminary experiments to test the *XBee* modules on the same scenario showed that the connectivity starts failing above 10 meters (Fig. 9). Therefore, to allow a more realistic and conservative approach, the connectivity between robots was maintained using the received signal quality. To that end, the *XBee* modules were modified in order to provide the *RSSI* signal output (*cf.*, Fig. 6b). This *RSSI* output is available as a pulse width modulation (*PWM*) signal of 120 *Hz* where the duty cycle DC varies accordingly to the signal level relative to the receiver sensitivity as it follows:

$$DC \approx 38 + 0.1 \times RSSI, \tag{7}$$

in which the parameters of the straight-line equation were obtained in the equipment datasheet [13]. For instance, a 30% duty cycle (*i.e.*, 1.5 *V*) is equivalent to approximately the receiver sensitivity of -94 *dBm*. In order to choose a minimum signal threshold that would ensure the *MANET* connectivity, Fig. 9 presents the relation between the *RSSI* and the distance between two robots randomly wandering in the same scenario presented in Fig. 8a while sending 30 periodic messages every 2 seconds to each other at each different distance. The *RSSI vs* the inter-robot distance was represented using a boxplot chart, in which the ends of the blue thicker lines and the circle in between correspond to the first and third quartiles and the median values, respectively. The numbers on top of each set of measures correspond to the number of messages received at each different distance.

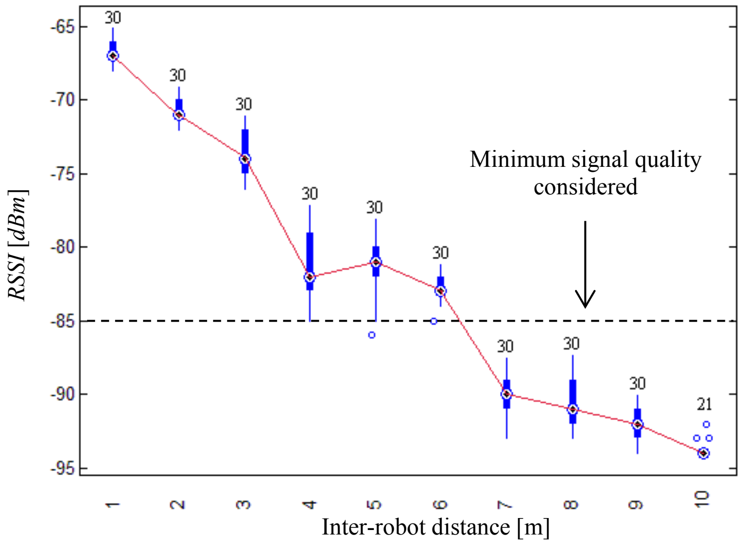


Fig. 9. Measured *RSSI* versus distance from two robots located in the experimental scenario.

As expected, in an indoor scenario endowed with obstacles, the signal quality is not proportional to the inter-robot distance. In fact, even the inverse relationship between distance and signal quality considered in many works does not match reality since the propagation model is more complex, *i.e.*, the signal depends not only on the distance but also on the multiple paths from walls and other obstacles. Moreover, for a distance above 10 meters, a robot is only able to receive approximately 2/3rd of the messages. Therefore, to avoid the possible loss of packets due to the distance between robots, the minimum allowed receiver power was set to -85 *dBm*, *i.e.*, for distances bellow 6 meters. This allows avoiding the possible loss of packets due to low levels of signal quality.

A minimum, initial and maximum number of 0, 3 and 4 swarms were used, thus representing an initial swarm size of $N_S = 5$ *eSwarBots*. The maximum travelled distance between iterations was set as 0.25 meters, *i.e.*, $\max|x_n[t+1] - x_n[t]| = 0.25$. In other words, each robot could only travel a maximum of 0.25 meters without considering the position of its neighbor robots so as to ensure the *MANET* connectivity.

As previously stated, by employing the optimized communication strategies from Section III and IV, it is expected to significantly reduce the communication cost of the *RDPSO* algorithm. One of the methods to evaluate the communication cost consists in counting the average number of packets sent and the processing time to handle the communication procedure, *i.e.*, pause time, for each robot over the 360 seconds of each trial. The number of packets sent was easy to retrieve since a robot under the “regular” *RDPSO* communicates after each iteration step to its own swarm, *i.e.*, if it is a swarm of 5 robots then the robot will send 4 packets, while in the “optimized” one the robot follows the rules presented in Section II. Regarding the pause time inherent to the whole communication procedure, a timer was used to count the time before entering the function that allows for a robot to send and receive the data packets from its own swarm. It is noteworthy that during that time the robot is unable to perform any other action. Table 2 compares the average (*AVG*) and standard deviation (*STD*) communication cost of the *RDPSO* with and without the proposed strategy.

Table 2. Communication Cost.

	AVG±STD Number of packets	AVG±STD Pause time [seconds]
“Regular” *RDPSO*	742±24	126±4
“Optimized” *RDPSO*	415±37	39±7

As it is possible to observe, the number of messages significantly decreases using the proposed methodology. This is highly valuable as the number of exchanged messages has a high influence on the power consumption of each robot. On the other hand, reducing the number of times each robot needs to share its information allows reducing the time allocated for such task. Note that this is not proportional since that, in the “optimized” *RDPSO*, robots communicate at each iteration step only to their neighbors (since *eSwarBots* are not equipped with sensing capabilities that allows retrieving teammates position). Communication to the whole swarm is constrained by how each robot improves over time. In other words, while each robot allocates approximately 35% of the mission time to exchange information within the “regular” *RDPSO*, this novel approach allows reducing this value to approximately 10%, thus increasing robots mobility. This is due to both requiring less data to be exchanged (Section III) but also the minimization of *route discovery* messages inherent to the *RDPSO* based *AODV* (Section IV). In other words, the herein proposed approach would be more power efficient and allow each robot to spend less time without moving than the “regular” one.

Nevertheless, the efficiency of a communication paradigm cannot be measured by only comparing the total number of exchanged packets. One of the most well-known performance metrics to evaluate the network throughput is the packet delivery ratio. The packet delivery ratio is calculated by dividing the number of packets received by a robot by the number of packets sent to it. This allows specifying the packet loss rate, which limits the maximum throughput of the network. Therefore, the average packet delivery ratio was evaluated based on the number of robots within the same swarm (either active swarm or the socially excluded group). As previously mentioned in Section III, and further detailed in [22], the *RDPSO* uses a "punish"-"reward" mechanism to avoid sub-optimality by socially excluding and including robots within active swarms. In other words, at some point over the 360 seconds of each trial, *i.e.*, 7200 seconds for each set, a swarm may be formed by only two robots or even by the 15 robots from the population. In other words, Fig. 10 depicts the average packet delivery ratio when swarms are formed by a specific number of robots, even if some of those cases, namely swarms formed by less than 3 robots or by more than 10 robots, only occur in some occasions (around 5% of the whole time).

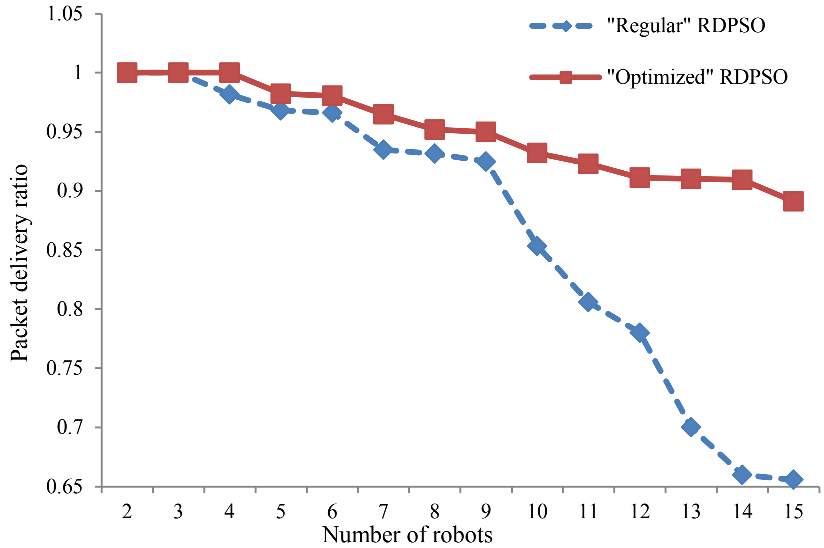


Fig. 10. Packet delivery ratio within robots from the same swarm.

As one may observe, there is a sharp decrease on the packet delivery ratio for the "regular" *RDPSO* when a swarm is formed by more than 10 robots, dropping down to approximately 65% for a maximum network load of 15 robots. This is explained by the high number of exchanged messages that, for a network load above 10 robots, does not satisfy the capacity of the buffer or the packet buffering time exceeds the time limit. As the "optimized" *RDPSO* significantly decreases the number of exchanged messages (*cf.*, Table 2), robots are still capable of receiving more than 90% of the data even within a swarm of 15 robots.

The first key contribution of this paper, *i.e.*, the efficient way to share information within the *RDPSO* algorithm (Section III), is the major reason for such significant reduction in both communication cost (Table 2) and number of dropped packets (Fig. 10). Although the adapted *AODV* improves the communication efficiency of the *RDPSO* algorithm, it is still not clear how advantageous this specific extension may be so far.

The routing overhead has been frequently used in the literature to evaluate routing algorithms, being commonly represented by the ratio between the number of *route discovery* messages and the number of data packets. Once again, let us compare the routing overhead of the "regular" *RDPSO* with the "optimized" *RDPSO* for each different teamsize from 2 to 15 robots under the 7200 seconds of each set of trials.

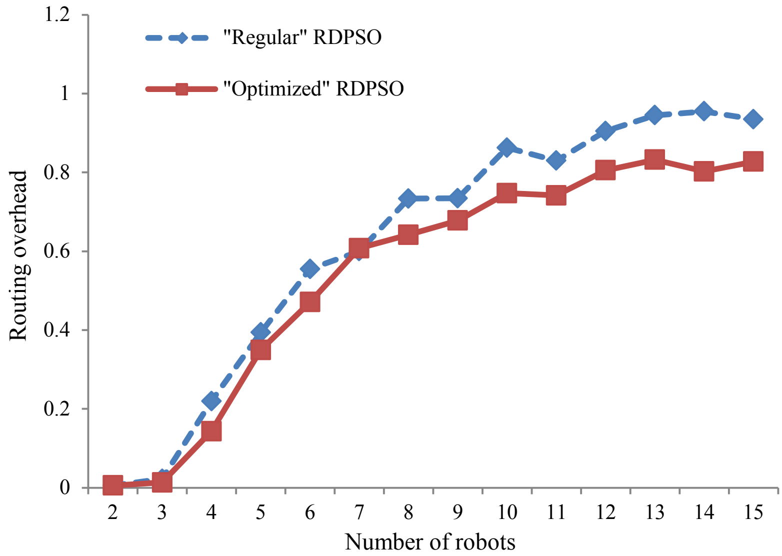


Fig. 11. Routing overhead within robots from the same swarm.

Once again, the "optimized" *RDPSO* clearly overcomes the "regular" one for larger population of robots. Even though the number of data packets is reduced due to the efficient way to share information between robots (Section III), the number of *route discovery* messages decreases more significantly (Section IV), thus resulting in a smaller routing overhead for a larger number of robots. It would be expected to have a worse routing overhead ratio when robots communicate less while they are moving since the routes would be completely outdated. Nevertheless, the *RDPSO* based *AODV* is able to reduce the number of *route discovery* messages in such a way that it allows overcoming that issue. This is due to the proposed geographically-based *AODV* that takes into account the dynamics of the *RDPSO*, thus creating on-the-fly routes (Fig. 7). However, how better are those new routes when compared to the alternatives returned by the traditional *AODV*? To answer that question, one needs to analyze the number of hops forming such routes.

The average hop count may be represented by the sum of the number of hops necessary to deliver the packets from their sources to destination divided by the total number of successful delivered packets. The average hop count is measured in number of hops.

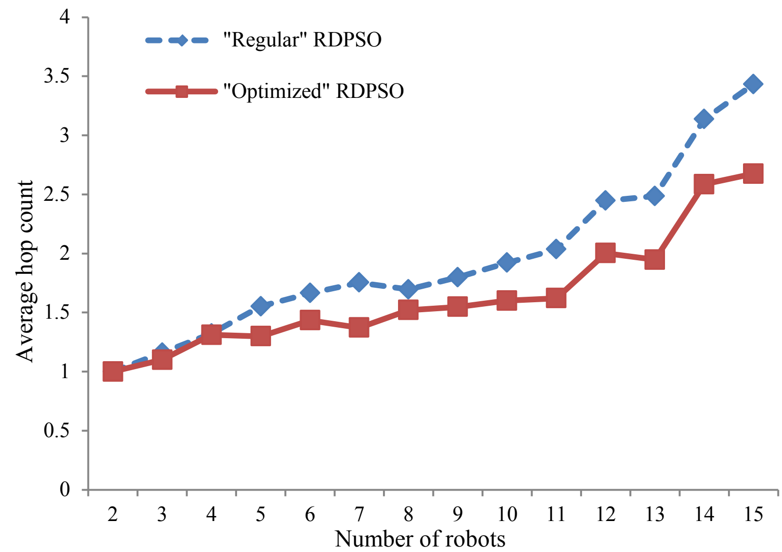


Fig. 12. Average hop count within robots from the same swarm.

As Fig. 12 depicts, the applicability of the novel *AODV* routing protocol may be observed for a swarm of, at least, 5 robots. For smaller swarms, the improvement of the *RDPSO* based *AODV* is meaningless which, on the other hand, turns out to be a worse alternative to the traditional *AODV* since it slightly increases the memory complexity of the algorithm (*cf.*, Section IV). However, as analyzing swarm algorithms within small populations may not represent the required collective performance (*cf.*, [43]), let us focus on larger teamsizes, *i.e.*, above 5 robots. As it is possible to observe, in some situations, the *RDPSO* based *AODV* reduces around 20% the number of required hops to deliver a packet. Although this may not seem relevant, this contributes to a smaller pause time and, consequently, a higher mobility of the robots. Moreover, reducing the number of hops necessary to deliver the packets also reduces the power consumption of each robot, thus increasing the autonomy of the whole swarm.

B. Temporal Analysis

It is noteworthy that the two key contributions of this paper, *i.e.*, the efficient way to share information within the *RDPSO* algorithm and the adapted *AODV* routing protocol, result in significant differences compared to its "regular" counterpart. Moreover, such differences increase with the number of robots, thus improving the scalability of the *RDPSO* algorithm. Yet, in order to further explore inter-robot communication dynamics under the "optimized" *RDPSO*, let us analyze how such information is shared within different social statuses, *i.e.*, within socially active and excluded swarms.

In order to achieve this, the number of local and global broadcasts within each swarm was analyzed. For a better understanding of how robots within the *RDPSO* evolve, let us take a look at one of the 20 trials in which the "optimized" *RDPSO* was evaluated, *i.e.*, a single trial of 360 seconds. Fig. 13 depicts the distribution of robots (Fig.13a) and highlights the respective total number of local (Fig. 13b) and global broadcasts (Fig. 13c) within each swarm over time. While the colored lines correspond to each socially active swarm, respectively *R* (red), *G* (green) and *B* (blue) swarms, the dark dashed line corresponds to the socially excluded swarm. The mission starts with 5 robots within each active swarm as previously stated. As one may observe, the number of workers in active swarms tends to decrease over time. This is an expected phenomenon as the resources begin to dwindle over time, *i.e.*, in this specific case study robots become unable to find ever improving light intensities. At some point it is even possible to observe that swarms *B* and *R* extinguish while swarm *G* proliferates, thus reaching a population of up to 11 robots. This happens right before the population in swarm *G* decreases to approximately 7 robots. Consequently, this leads to an increase of socially excluded robots with a maximum of 10 robots after the 4th minute. Regarding the local broadcasts, such temporal variations would be expected by considering the rules previously stated throughout Section III. The local broadcasts necessary to maintain the network connectivity remain at each step of the algorithm, thus presenting a proportional amount to the number of robots within each swarm. Such proportionality is only broken when a socially active swarm claims a new robot or tries to create a new swarm (small peaks observed in the colored lines). A rationale behind the global broadcasts is harder to achieve. As one may observe, in general, socially active robots present a higher amount of messages flooded through the whole swarm. This is interesting to observe as such global broadcast is related to swarms' improvement that requires the global consent of the population. As a result, such global broadcasts diminish over time. This kind of global message seems to be significantly less recurrent in socially excluded swarms.

As one may observe, the time a certain amount of robots is socially excluded may not correspond to the time that the same amount is socially active. Therefore, to further compare the information shared within the different social statuses over the 7200 seconds of the whole set of experiments, a simple normalization of the data over time was adopted. Fig. 14 depicts the average number of local and global broadcasts within each swarm configuration. As a rule of thumb, the local broadcasts increase almost proportionally to the population of robots. This may be observed in both socially excluded and active swarms with a minor difference between both. The main difference between robots belonging to different social statuses may be seen in the number of global broadcasts. Socially excluded robots barely communicate to the whole group. In fact, such communication only depends on the improvement of socially active swarms if socially active swarms improve. Hence, as the overall amount of socially active robots decreases, the number of socially excluded robots increases and the probability of success (*i.e.*, improving the current solution) also decreases. Consequently, this reduces the required number of global broadcasts from excluded swarms.

a)

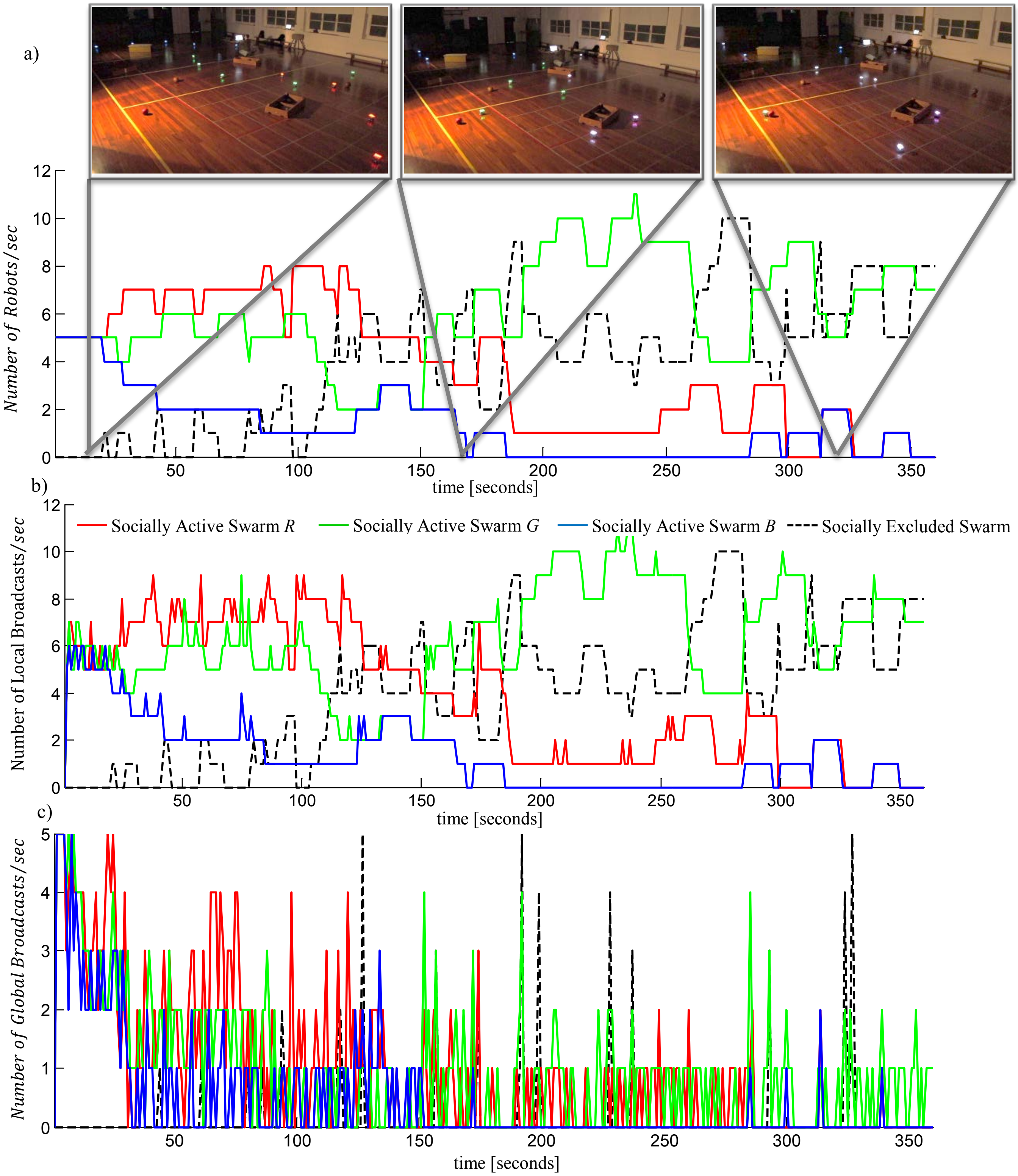


Fig. 13. Evolution of robotic swarms over a trial of 360 seconds. a) Population size; b) Number of local broadcasts; c) Number of global broadcasts.

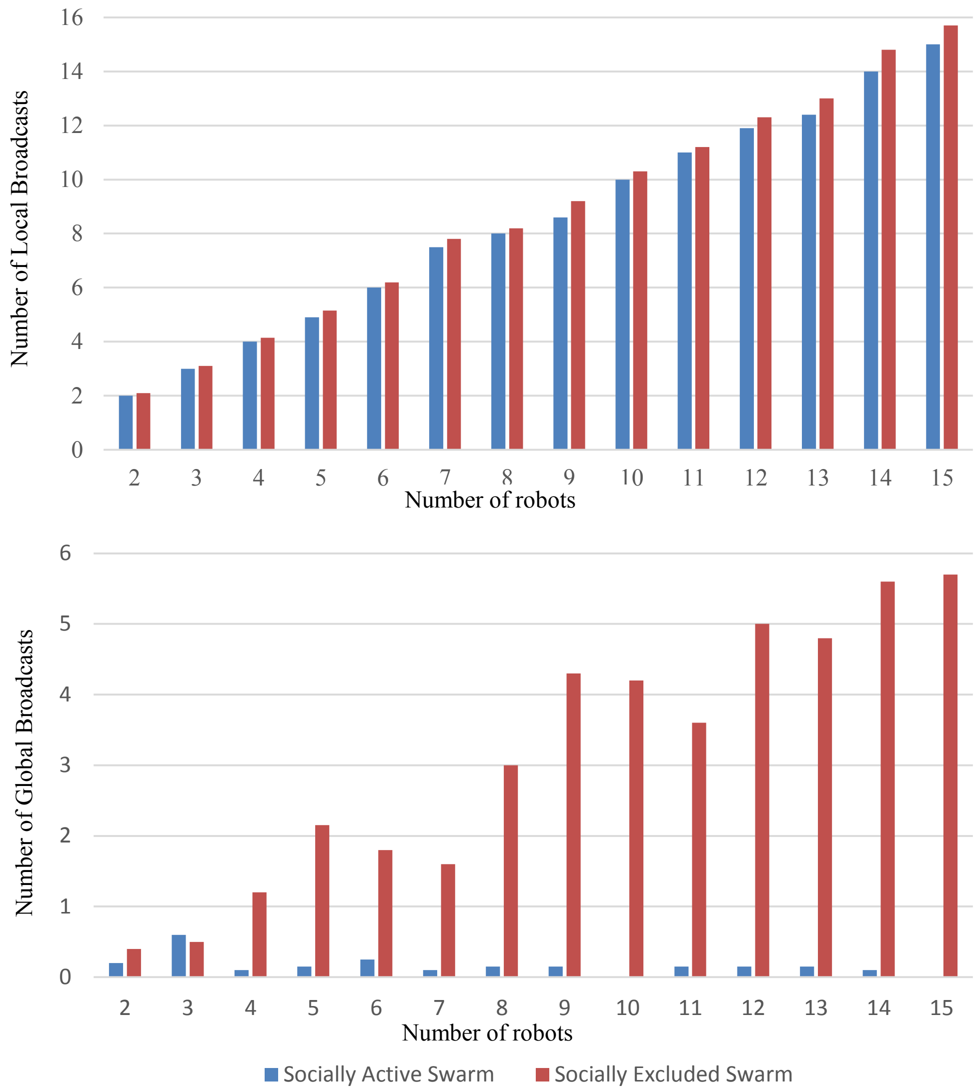


Fig. 14. Normalized temporal average number of local and global broadcasts.

As the experiments presented so far are limited to a maximum number of 15 physical robots within the same swarm, it was necessary to perform simulation experiments to evaluate the scalability of the "optimized" *RDPSO*.

C. *Scalability Evaluation through Simulation*

The *Multi-Robot Simulator* (*MRSim*)[1] was used to evaluate the previously proposed "optimized" *RDPSO*. *MRSim* is an evolution of the *Autonomous mobile robotics toolbox SIMROBOT* (*SIMulated ROBOTs*) previously developed for an obsolete version of *MatLab* [44]. The simulator was completely remodeled for the latest *MatLab* version and new features were included such as mapping and inter-robot communication [45]. In addition, *MRSim* also enables the addition of a monochromatic bitmap as a planar scenario and configuration of its properties (*e.g.*, obstacles, size, among others), as well as implementation of features for each swarm robotic technique (*e.g.*, robotic population, maximum communication range, among others) and configuration of the robots' model (*e.g.*, maximum velocity, type of sensors, among others).

Due to the lack of a preexistent model of *WiFi* propagation (radio frequency at $2.4\ GHz$) in *MRSim* simulator, this work considered its implementation based on Luca *et al.* work [46]. The attenuation over the transmitter-receiver distance $d\ [m]$ was calculated as:

$$L = l_c + 10\gamma \log d + \sum_W l_W, \tag{8}$$

[1]http://www.mathworks.com/matlabcentral/fileexchange/38409-mrsim-multi-robot-simulator-v1-0

wherein W represents the number of walls with attenuation l_W between the transmitter and the receiver. The constant factor l_c corresponds to the reference loss value at 1 m. This was defined as $l_c = 47.4\ dB$ and experimentally validated in indoor scenarios by Luca *et al.* [46]. The path loss exponent γ is usually defined between 2 and 4, wherein values near 2 correspond to propagation in free space and values near 4 represent lossy environments. The parameter γ was uniformly distributed over the interval 3 and 4, thus providing a stochastic effect on the communication propagation [47].
In order to improve the understanding of how *WiFi* communication propagates in the scenario considered in this work, Fig. 15a depicts the range of communication power. Note that signal strength values are shown in dBm. As it is possible to observe, and considering the condition that the minimum receiver power allowed was set to -85 dBm (Fig. 9), a robot may be unable to communicate with its teammates in some zones due to occlusion by obstacles and distance.

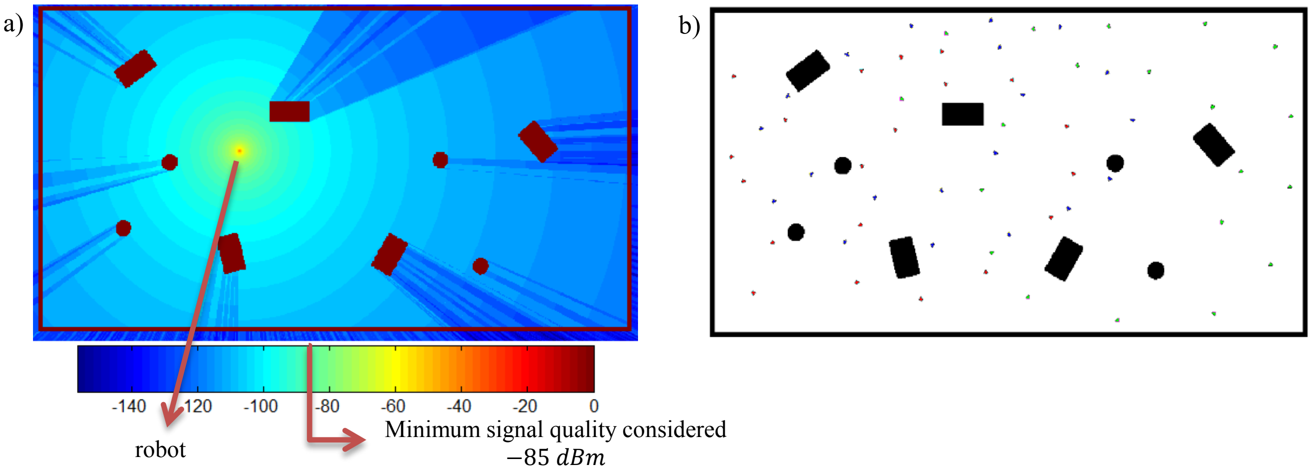


Fig. 15. Simulation experiments in a 20 × 10 meters indoor scenario (sports pavilion): a) *WiFi* communication propagation; b) Setup with 3 swarms of 20 robots each (population of 60 robots) autonomously deployed based on the *EST* approach in [12].

As a means of simplification and in line with the previous real experiments, the same 20 × 10 meters indoor scenario (sports pavilion) was created on *MRSim*. Due to the computational cost of the simulator, which significantly increases with the number of robots, only experiments of up to 60 robots were possible to carry out.

As *MRSim* is a step-based simulator (without real time iterations), the ratio between the number of packets exchanged within the "optimized" and the "regular" *RDPSO* was analyzed. Note that this depends on the type of communication (*i.e.*, local or global broadcast). For instance, in a swarm of 10 robots a global broadcast from a single robot corresponds to 9 packets exchanged, *i.e.*, one for each teammate. However, if that same robot has only 4 neighbors (one-hop robots) then a local broadcast will correspond to only 4 packets exchanged. Due to the stochastic nature of the *RDPSO*, boxplot charts were once again used to represent the ratio between the number of packets exchanged within the "optimized" and the "regular" *RDPSO* over the 30 trials with a maximum of 5000 steps each (Fig. 16). To easily observe the differences, the ratio was averaged at each 100 steps. Once again, note that the number of robots within the same swarm may vary from 2 robots to the total number of robots within the population (60 robots).

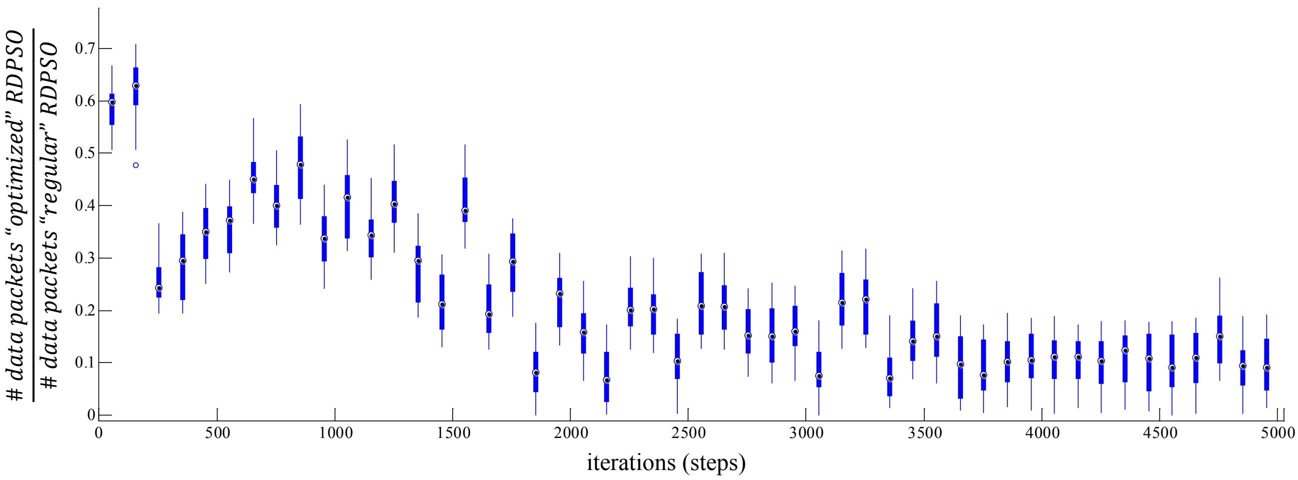


Fig. 16. Ratio between the number of packets exchanged using the "optimized" *RDPSO* and the "regular" *RDPSO* over the number of iterations in a population of 60 robots.

As one may observe, the difference between the "optimized" and the "regular" *RDPSO* grows with time. The decreasing tendency observed in Fig. 16 is an expected phenomenon. As swarms exploration within the "optimized" *RDPSO* advances, the number of global broadcasts necessary to converge to the optimal solution decreases (Section III-E). After a certain amount of time (half the mission time), the "optimized" *RDPSO* is able to decrease the number of exchanged data packets to approximately 20% of the number of data packets exchanged under the "regular" *RDPSO*. In terms of communication cost this may be considered as a significant improvement. As an example, the *eSwarBots* platforms usually present a battery autonomy of up to 4 hours without using the *XBee Series 2* modules. However, such autonomy drops to approximately 2 hours with constant data transmission [13]. Another example such as the well-known *e-puck* robot is even more significant [48]. The *e-puck*'s battery autonomy can drop from 3 hours to approximately 1 hour using the *WiFi* communication from the *Gumstix Overo COM*.

VI. Discussion – Towards a *Stigmergetic RDPSO*

The Robotic Darwinian Particle Swarm Optimization (*RDPSO*) was proposed for the first time in 2011 [22] by adapting the Darwinian Particle Swarm Optimization (*DPSO*) [23] to swarm robotic applications. Although the communication between robots was initially studied in Couceiro *et al* [9], previous works have been mainly focused on improving the evolutionary properties of the *RDPSO*, thus neglecting the scalability constraints that those may impose. Therefore, the authors would like to discuss the take-home message this paper brings forth and present future expectations around the *RDPSO* algorithm.

The motivation behind this work was to explore a strategy for improving the scalability of the *RDPSO* by optimizing its communication complexity. This was achieved by analyzing judiciously the information to be explicitly exchanged between robots and proposing a way to efficiently share it without decreasing the collective performance of the algorithm. Afterwards, the well-known Ad hoc On-demand Distance Vector (*AODV*) was adapted based on *RDPSO* dynamics.

Real and simulation experiments were conducted to observe the effect of the proposed optimized strategy. The mission consisted of collectively exploring a $20 \times 10\, meters$ scenario in which robots' cognitive solution was affected by the light sensed at their current position. The superiority of the "optimized" *RDPSO* over the "regular" one was especially visible in the number of packets exchanged between robots and the packet delivery ratio. Although the differences between the routing overhead and the required number of hops to deliver a packet were not significant for small groups of robots, the "optimized" *RDPSO* was still able to reduce both to approximately 20% less for swarms of 15 robots. Those differences were even more visible in the simulations with a swarm of 60 robots examining the ratio between the total number of packets exchanged within the "optimized" and the "regular" *RDPSO*. Although in the beginning of the mission the "optimized" *RDPSO* presented a rather modest reduction of approximately 50% of the number of packets exchanged, as robots continuously explored the scenario such differences increased to approximately 85%. To improve the analysis of the communication architecture within the *RDPSO*, the differences between the two social statuses were also represented, thus revealing that the principle of cooperation undergoes several phases that depend on more than just mission-related contextual information (*e.g.*, sensed solution).

This dependency between the swarms gives rise to a *competitive evolutionary process* inherent to animal nature as described in the Darwinian survival-of-the-fittest. On the other hand, as many other biological societies involved in diverse survival conditions, the outcome of this competitive evolutionary process is reflected into social cooperation among the members from the same group. This is a highly recurrent process in nature denoted as *coopetition* [49]. For instance, certain birds are unable to reach parasites on some parts of their bodies, thus benefiting from preening one another. Hence, there is an entire flock of potential preeners which compete in hopes of establishing a beneficial cooperative relationship. To the similarity of the *RDPSO*, birds that try to be preened without preening others are excluded from these relationships as they do not compete.

Those results paved the way towards an insightful reassessment and revolution of the *RDPSO* algorithm. Considering the recent advances in the control of aggregation behaviors without communication (*e.g.*, [5]), the most expected improvement would be the development of a *stigmergetic RDPSO* without significantly reducing the collective performance of the swarms. In this case, the macroscopic capabilities of the *RDPSO* should be defined by spatial or dynamical conditions in the environment. In other words, the system and environment itself build a closed macroscopic feedback loop, which works in a collective way as a distributed control mechanism [5]. In this case, robots interact kinetically or through *stigmergy* effects [50]. For instance, emulating Darwin's survival-of-the-fittest without explicit communication would not only require robots to possess the capability of discerning collisions between obstacles and other robots, but also between robots from different swarms. Such could be attained by endowing robots with simple low-cost vision capabilities such as the ArduEye vision sensor[2].

All that being said, one may state that it is still difficult at this point to go from an algorithm sustained by explicit communication to a *stigmergetic* one. However, the authors argue that this paper provides an exhaustive rationale on the necessary explicit communication within the *RDPSO* that gives the first step in that direction.

[2] http://ardueye.com/

VII. Conclusion

An optimization of the communication procedure between robots under a collective swarm intelligence behavior, previously proposed and denoted as Robotic Darwinian Particle Swarm Optimization (*RDPSO*), was presented in this paper. Moreover, the traditional Ad hoc On-demand Distance Vector (*AODV*) was improved considering robots' motion and behaviors inherent to the *RDPSO*. Such improvements were motivated by the need to use large teams of robots without significantly increase the communication overhead. Several experimental results with up to 15 real robots and 60 virtual robots in a 20×10 meters scenario clearly show the advantages of such an optimized strategy regarding the scalability of the algorithm, thus paving the way for future swarm applications of hundreds or thousands of robots. Therefore, in the future, and due to the flexibility of the herein proposed solution, this "optimized" *RDPSO* should be evaluated on larger teams of swarm robots under realistic applications such a multi-robot Simultaneous Location and Mapping (*SLAM*) that usually presents a communication bottleneck as the number of robots increase. Finally, we also intend to implement an estimation method to dimension the swarm of robots according to the environment topology and temporal constraints.

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