V. Experimental Results

In this section, the effectiveness of using a modified version of *PSO* and *DPSO*, respectively denoted as *RPSO* and *RDPSO*, on a group of agents (*i.e.*, robots) performing distributed unsupervised learning with local and global information is explored. The number of robots is equal to the number of particles in the population, so each robot is represented by a single unique particle. Robots are randomly deployed in the search space. Since both *RPSO* and *RDPSO* are stochastic algorithms, every time they are executed they may lead to different trajectory convergence. Therefore, multiple test groups of 250 trial of 350 iterations each were considered. In the particular case of the *RDPSO*, it is used a minimum, initial and maximum number of 1, 3 and 6 swarms, respectively (represented by different colors in Fig. 3), independently of the population of robots taking into account the algorithm description in section IV where the number of swarms may vary throughout the simulation. In these experiments, the search space is represented by an example of a Gaussian distribution on a function of two variables of the search space, *x* and *y*-axis, which represents the position of the robot in meters. The optimum value of this function (-6.54 in the example) is represented in Fig. 5 by a dashed line. Robots will then move in a scenario of size 30 x 30 meters where the *z*-axis represents the value of the objective function. In this specific case, the objective of the particles is to find the minimum value of the cost. Both algorithms will be evaluated by changing the density of obstacles and the number of robots (*a.k.a.* population) using boxplot charts which is a quick way of examining the final result of each trial graphically. Experiments are then divided into three types: *i*) without obstacles; *ii*) with a regular density of obstacles randomly deployed at each trial; and *iii*) with a high density of obstacles randomly deployed at each trial (*cf.*, Fig. 3). The experimental results obtained without obstacles are used as guidelines for a better understanding of the impact of obstacles in the algorithm's performance since both algorithms performed efficiently without obstacles and obtained the optimal solution. The number of robots will vary from 3 robots to 33 robots with incremental steps of 6 robots, *i.e.*, $N = \{3,9,15,21,27,33\}$ in order to understand the performance of the algorithms related to the population size (Fig. 4). The ends of the blue boxes and the horizontal red line in between correspond to the first and third quartiles and the median values, respectively.

As expected, the rise in the number of obstacles leads to a decrease of performance in both algorithms, for a robot population inferior to 21 robots. It is also clear that the *RPSO* gets stuck in the local optimum (in the neighborhood of 0 and -3), thus increasing the inconsistency of the final result obtained (larger blue boxes and whiskers). This performance gets better as the number of robots rises. It is also verified that for $N \geq 27$ the algorithm tends to stabilize and the impact of the presence of obstacles in the algorithm performance is diminished as robots always arrive at the desired destination. The data distribution, despite the considered trial, turns out to be positively skewed (*i.e.*, the mean is higher than the median). This means that, in this case, as the goal is to minimize the cost function, 50% of the trials are around the desired objective value. Nevertheless, the *RDPSO* shows a better performance when compared with the *RPSO* in the three experimental datasets, being the median (red line) closer to the objective value, regardless of the number of robots.

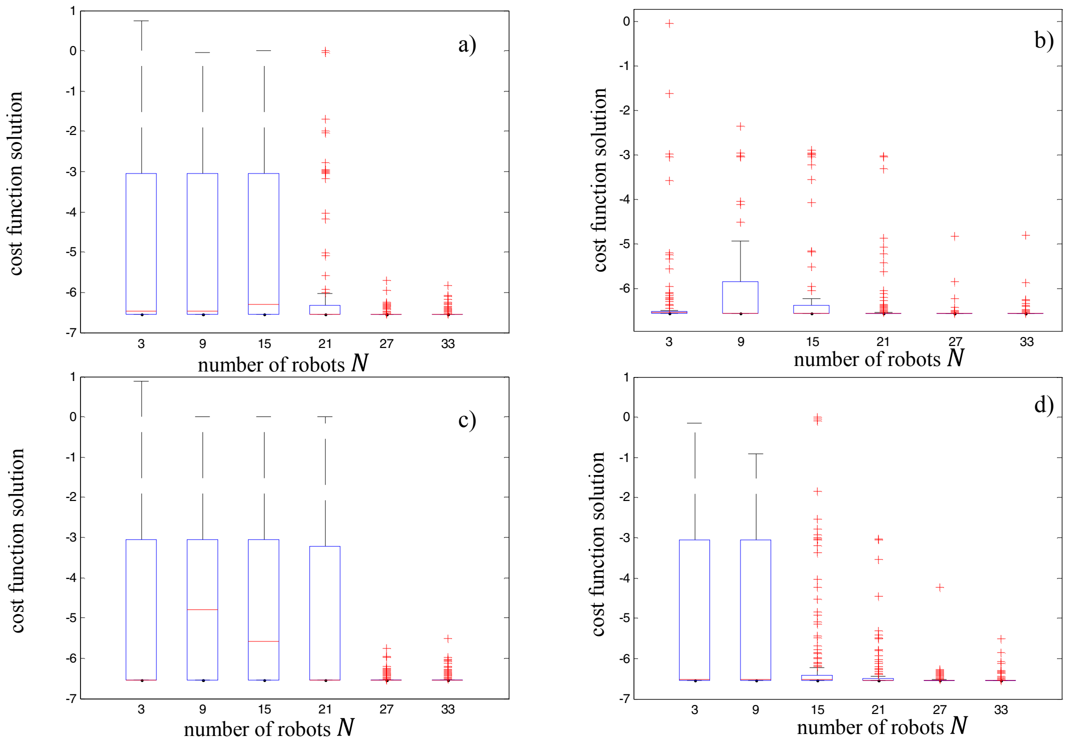

Fig. 4. Performance of the algorithms changing the number of robots *N* in the population; a) *RPSO* b) *RDPSO* with a regular density of obstacles; c) *RPSO* d) *RDPSO* with a high density of obstacles.

Since these simulation experiments represent a search task, it is necessary to evaluate not only the completeness of the mission but also the speed. Therefore, to further compare both algorithms, the convergence of the *RPSO* and *RDPSO* can be analyzed for the worst case scenario, *i.e.*, for a high density of obstacles. As Fig. 5 shows, the median of the best solution in the 250 simulation was taken as the final output for each value in the set $N = \{3,9,15,21,27,33\}$. Once again, the performance of the *RDPSO* turns out to be better than the performance of the *RPSO*, with a full convergence to the desired objective value at time $t = 50$, regardless of the number of robots considered. This can be explained due to the effect of social exclusion/inclusion described in section IV which main goal is to avoid being stuck in local optima. In the *RPSO* algorithm it is verified that sometimes it gets stuck in local minimum.

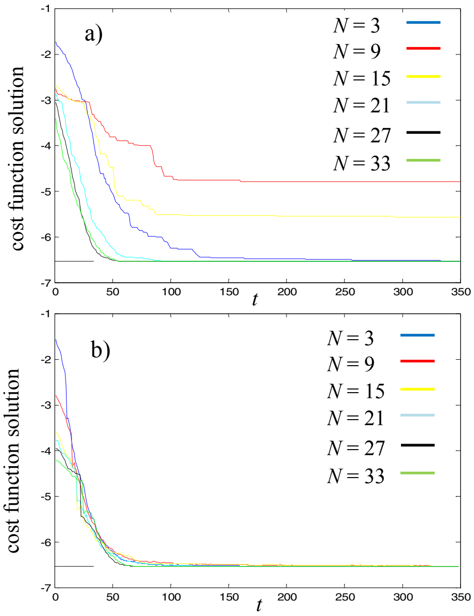

Fig. 5. Convergence of the algorithms changing the number of robots N in the population with a high density of obstacles; a) *RPSO*; b) *RDPSO*.

VI. Conclusion

Modified versions of the Particle Swarm Optimization (*PSO*) and the Darwinian *PSO* (*DPSO*) algorithms based on obstacles avoidance abilities and real-world multi-robot systems (*MRS*) characteristics were developed and respectively named as *RPSO* (Robotic *PSO*) and *RDPSO* (Robotic *DPSO*). The features presented in this document were implemented in a *MatLab* environment and experimental results show how the performance of a *MRS* with a biologically inspired behaviour based on natural selection and social exclusion, as in the *RDPSO*, increases when compared to the *RPSO*. One of the future approaches will be the extension of the *RDPSO* taking into account communication constraints, in a parallel distributed fashion for exploration tasks in *MRS*. Since robots may move to areas of far distance, 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 in order to relay information from one point to another.

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