Multi-robot exploration using Dynamic Fuzzy Cognitive Maps and Ant Colony Optimization

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***Abstract*— An application field of Multi-Robot Systems (MRS) is within victim rescue operations. The main challenge faced by disaster rescue teams is response time. The chances of finding survivors decrease significantly over time and dramatically decrease after 48 hours. In this context, the motivation of this work is to present an MRS inspired by the concepts of swarm robotics to rescue victims in unknown environments. In this case, the robots are unaware of the search area boundaries and obstacles, knowing the number of victims to be rescued as a stopping criterion for the simulations made in Matlab®. Therefore, three approaches inheriting the main aspects of fuzzy logic are used based on previous works: a fuzzy logic controller (FLC), a dynamic fuzzy cognitive map (DFCM) controller, and a DFCM inspired by the ant colony optimization metaheuristic (DFCM-ACO). The proposed task simulates real life disaster rescue operations, or even humans lost in unfamiliar environments such as forests. The simulations were performed in three environments in order to test the overall robustness against unpredictable situations, autonomy, explored area and processing time for both approaches using a subsumption-based architecture. In general, the results suggest that the DFCM-based MRS approaches are able to complete the tasks consuming less processing time, with robots travelling shorter distances to explore a similar environment to the FLC approach and with the DFCM-ACO presenting balanced results between the other techniques. Finally, future works are outlined.**

Keywords—swarm robotics, multi-robot system, dynamic fuzzy cognitive maps, ant colony optimization.

I. INTRODUCTION

Autonomous robotics has recently emerged as a recurring theme due to its participation in Industry 4.0 concepts. This term was created in 2011 and, in short, refers to the fourth industrial revolution. It has three basic principles: cyber-physical systems, internet of things (IoT), and smart factories [1].

In Industry 4.0, industrial machines or active systems are characterized by the use of intelligent networked systems in order to provide greater flexibility, efficiency and integration with the entire production chain. In this way, robots can promote data and information sharing and perform specific activities [2].

Therefore, these entities may be aligned with mechanical functions in logistical collaboration, variable monitoring issues, and identification and search for victims of large-scale accidents. From the extensive knowledge of the environment, with the large amount of information obtained (big data), it is possible, through intelligent systems (such as those used in this work), to make decisions with greater precision in a collaborative way.

An example of this case occurs in space, where we can highlight the semi-autonomous rovers of the Curiosity expedition to Mars, active since its launch in 2012. An operator controls from Earth the details of each mission (routes and scientific experiments to be performed), while that rovers have obstacle avoidance capabilities. This is due to the time difference between the operator command and its receipt by the rovers (response time), which could cause damage to these vehicles. In this case, autonomous navigation requires the integration of depth measurement with a vision system, through stereo vision analysis or other range-determining methods. It also requires heuristic behavioral rules for the device to navigate in this unknown environment [3].

Thus, the use of multi-robot systems (MRS) and their subdomains, such as swarm robotics, has gained prominence in the mobile robotics landscape. In this type of system, multiple robots are employed to perform common tasks in shared environments [4]. However, while these robot teams may be more effective, they also present new challenges. Robots may have nonholonomic kinematics; Information captured by sensors may be limited, and external noise and disturbance may make it difficult to process available information. Thus, it can be said that maintaining various objectives and merging sensory information are non-trivial design challenges [5].

One of the possible uses of MRS is within victim rescue operations, a recurring scenario today. The main challenge encountered by disaster rescue teams is response time. Rates of finding surviving people and/or animals decrease significantly over time and, due to factors such as dehydration and injury, are dramatically reduced after 48 hours [6]. Therefore, rescuers need to move as quickly as possible, avoiding static and dynamic obstacles, and covering the largest area to reach all potential

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victims to save their lives [7]. An emerging alternative to the use of human first responders is emerging in disaster rescue (DR) or search and rescue (S&R) robots.

Tasks of S&R robots are characterized by scenario exploration and require the determination of all victims ' locations in order to significantly reduce the chances of harming rescuers' lives. These restrictions make S&R robots challenging tasks for humans, and one possible solution to the disadvantage is the use of robot systems, in particular MRS [6].

However, due to their relative novelty, S&R robots have not been widely adopted. Between 2001 and 2012, robots or MRS were used 37 times in meteorological, geological, mining, and human disasters, with success in 81% of cases. Since 2012, there has been a steady increase in the use of MRS in disasters, with their use in approximately 30 cases in six countries, mainly in mining and buildings collapses [7].

Several papers dealt with MRS exploration and rescue scenarios. A collective foraging task was achieved by MRS in [8], in which a decision-making mechanism and a fuzzy control system were presented to provide robots' behavior, aiming at a trajectory planning, designed to avoid collisions. This behavior is inspired by the actions of ants and other social animals in their search for food and resources for their nests [4]. Another example of foraging behavior is presented in [9], bio-inspired by the slime mold aggregation strategy. In this work, the main cooperative task consists of garbage finding and disposal in desired locations, whereas the sub-tasks include scenario exploration, path finding and information propagation.

The objective of this work is to develop an autonomous MRS capable of performing search tasks in simulated environments. Robot movement and orientation control will be accomplished by three fuzzy logic strategies: a Mamdani fuzzy logic controller (FLC), a dynamic fuzzy cognitive map (DFCM) - both from a previous work [10] – and a DFCM inspired in the ant colony optimization (ACO) metaheuristic (DFCM-ACO), which is exploited in this research study.

The authors expect this work to contribute to the intelligent systems area, hence applying the DFCM-ACO to a navigation system for semi-unknown environments exploration, victims rescue and its robustness verification, test a possible stress (8 robots) by contacting certain scenarios. The main advantage of this approach is that the processes of knowledge acquisition and representation are simplified using DFCMs. With the ACO use, the authors expect to enhance last paper's results by means of the robots' paths being more distributed (optimized) in comparison with the other approaches.

The remainder of this work is organized as follows: Section II compiles the overview of disaster-rescue and multi-robot systems. In Section III, the authors present development of the FLC, DFCM, and DFCM-ACO architectures. In Section IV, the results of all simulated scenarios are presented and compared to the previous work [10]. Finally, Section V concludes this work and addresses expected future contributions.

II. Multi-robot and Swarm Systems

The research area of multi-robot systems (MRS) encompasses the use of a set of robots to perform behaviors that converge towards the achievement of a common goal, whether on land, water or air [7]. In turn, one of the definitions for the term "swarm robotics" is given as the set of nature-inspired techniques for controlling large groups of relatively simple structural nature robots. Examples of swarms in the wild can be seen in a flight of birds or in a shoal [11], [12]. In this MRS field, robots often do not know the actions of other distant robots, i.e., communication is only between nearby robots, depending on stigmergy most of the time [7].

A stigmergic system has a process that undergoes changes with each transformation in the environment. In other words, the characteristics of the environment serve as stimuli to the behaviors of the system. In natural swarms, stigmergy is often the driving force behind phenomena such as ant trails. Therefore, stigmergy is an important field of research in swarm robotics, for example in artificial pheromone trails, as seen in this work [13].

Thus, based on the concepts of repulsive artificial pheromones, this work presents an optimization of the robots' trajectory, thus increasing the search area without increasing the distance traveled. In other words, when a robot detects high concentrations of pheromones – whether they are left by the other robots or itself – it will deflect its course so as not to become trapped in relatively more difficult navigational zones such as narrow corridors.

These concepts are part of ant colony optimization (ACO), a metaheuristic for combinatorial optimization problems presented by Marco Dorigo and his collaborators [14], [15]. ACO was inspired by ants' foraging behavior and, in particular, how they can find shorter paths between food sources and their nests. When searching for food, ants initially explore the area around the nest at random [16].

From the observation of their behavior, it was found that communication between the ants that walked the same trails occurred through a chemical called pheromone. As they move, they leave a pheromone trail on their path. Thus, the next ants decide which path to follow by the amount of pheromone detected, i.e., choose the path most used by the group [15]. As the pheromone evaporates over time, the higher the concentration of ants on one path, the more attractive it will be for the next ones [17].

Another feature needed for swarm MRS concerns the difficulty of the proposed tasks: the use of a robot swarm is only necessary if the tasks can only be performed at team level, or if completion time is a determining factor for the swarm. achievement of objectives. In other words, increasing the number of robots in a group can significantly reduce task completion time [18].

Robots in an MRS can have different types of behaviors, such as grouping, threading, searching, aggregating, and foraging. These behaviors are classified into collective (this work, as discussed earlier); cooperative, where robots are aware of each other; collaborative, when each robot helps others achieve their goals, and coordinative when robots are aware of others but do not share a common goal [19].

Another aspect inherent in swarm robotics is movement coordination. It can be related only to other robots, the environment, external agents and combinations of them [6], [7]. In this paper, robot movements are related to the three categories discussed: they change their movements due to other robots, static and dynamic obstacles (environment) and victim detection (external agents).

Other concepts of swarm robotics were also used to develop the simulations in this work. Robots are redundant (i.e., easily interchangeable) and coordination is decentralized: the loss of one robot is immediately compensated for by others and/or the deployment of another agent, not disrupting system operation. Finally, structural and component simplicity was aimed at facilitating repairs and reducing implementation costs, resulting in a less fault-prone system [20].

In this paper the perception of the MRS is distributed, so as to enable robustness against local environmental disturbances (dynamic obstacles). The proposed system also has a local communication algorithm, responsible for the only information that the robots share among them: the number of victims already rescued – to stop simulations when the robots find all the victims – and the obstacles already detected. Finally, memory algorithms store the position and direction of each robot for mapping environments.

With these features, robots are expected to have sufficient autonomy to operate in unknown or semi-unknown environments. For example, the flexibility to operate under noise or malfunction sensors, robot failure, dynamic environments and stress scenarios.

III. Robots' Architecture and Control strategies

The robots are modelled through a subsumption-based architecture, as seen in [10], with gathered aspects of the original one proposed by Brooks [21], in which a robot must be reactive only to external stimulus, not comprehensively. In this architecture, the global behavior (high-level) is decomposed into sub-behaviors of lower complexity levels. That approach is justified by Zadeh's incompatibility principle [22], and it is present in Braitenberg's vehicles work [23]: the increasing in a system's complexity is directly proportional to the difficult to foresee its behavior.

In short, the controllers' outputs generate the motors' pulses (w_L and w_R, 0 to 100%) of left and right wheels, respectively, according to each sub-behavior strategy. If both pulses are positive, the robot moves forward. If $w_L > w_R$ it turns right, and vice versa. Finally, a robot spins if one pulse is negative and the other one is positive [10]. The inputs are the actual data obtained from three ultrasonic sensors – frontal (*FS*), left (*LS*), and right (*RS*) – located in the front of the robots. These sensors have 12 cm of range, beam angles of 45º, and a white noise in order to verify the robustness of FLC, DFCM and DFCM-ACO.

The authors used the kinematic model given by (1) and (2) to develop this work: two powered front wheels and a dummy back wheel to stabilize the turns. *V* and *w* correspond to the robots' linear and angular velocities, respectively, b is the axis length (14.4 cm), R_R and R_L are the radius of rotation of the wheels (2.5 cm). The indices *R* and *L* denote the right and left wheels, respectively. Thus, the integration between the intelligent systems and the kinematic model is performed by interpreting the values of the ultrasonic sensors from the FLC, DFCM and DFCM-ACO, responsible for providing the angular velocities w_L and w_R applied in (2) to move the robots.

$$v_{R,L}.dt = w_{R,L}\,.[R \pm (b/2)]\,dt \qquad (1)$$

$$\begin{bmatrix} v \\ w \end{bmatrix} = \begin{bmatrix} (R_R/2) & (R_L/2) \\ (R_R/b) & (-R_L/b) \end{bmatrix} . \begin{bmatrix} w_R \\ w_L \end{bmatrix} \qquad (2)$$

The use of kinematics in this work instead of dynamic modeling is justified by its results matching in this application and its lower computational complexity [24]. Thus, as one of the principles of swarm robotics and MRS is simplicity of implementation, the authors opted to use kinematics to simplify simulated experiments to compare the proposed techniques.

The proposed paper uses the same approach of previous work [10]. The MRS have three tasks: 1) to detect and avoid static and dynamic (other robots) obstacles; 2) locate and rescue all the victims, and 3) map the environments. To complete these tasks, the global behavior was divided into four sub-behaviors, according to emerging system needs. These behaviors are described in detail in the authors' previous work [10]. Sub-behaviors 1 to 4 are respectively: free movement, obstacle avoidance, imminent collision scenario, victim rescue operation.

The sub-behaviors operate in parallel, each one implemented individually according to the finite-state machine shown in Fig. 1, and its events described in Table I. As seen in Fig. 1, the sensors' actual data inhibits or activates the sub-behaviors routines, generating the desired outputs of the controllers [10].

TABLE I. Events Description

Event	Description
A	Obstacle detected by any ultrasonic sensor
B	The three ultrasonic sensors detected an obstacle within the robot's safety zone (4 cm)
C	The robot found a victim
D	Victim found on the way to being rescued
E	Activation of the robot's memory algorithm

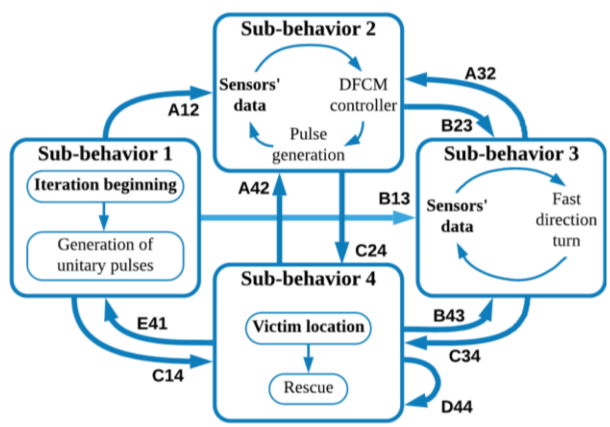

Fig. 1. Finite-state machine of the robots' operation.

In the three simulated environments, a group of 8 robots must rescue the victims, map the environment, and avoid collisions with static and dynamic obstacles (other robots). The simulations were performed in Matlab® software. The PC used has the following specifications: eight-core CPU, 16 GB RAM, and a SATA 3 SSD (R: 500MB/s, W: 350MB/s).

The authors used three control strategies for the MRS. The first one is a FLC with 3 inputs (ultrasonic sensors) and 2 outputs (pulses to the wheels), containing 125 rules adjusted on empirical trial [25]. The second one, described in more detail in [10], is a DFCM with 5 concepts based on the FLC approach. Finally, a more complex DFCM is presented in this work using concepts of ACO. The DFCM-ACO contains 8 concepts – adding the pheromone detection in a similar way as done with the ultrasonic sensors: frontal, left and right pheromone positions, respectively FF, LF, and RF.

Fuzzy cognitive maps (FCMs) are a soft computing methodology that came as a combination of fuzzy logic and neural networks. They constitute a computational method that is able to examine situations where human thinking process involves fuzzy or uncertain descriptions. An FCM can be defined as a graphical representation, used to describe the cause and effect relations between nodes, thus giving us the opportunity to describe the behavior of a system in a simple and symbolic way.

In order to ensure the operation of the system, FCMs embody the accumulated knowledge and experience from experts who know the way the system behaves in different circumstances. FCMs possess certain advantageous characteristics over traditional mapping methods; they capture more information in the relationships between concepts, are dynamic, combinable, tunable and express hidden relationships.

The resulting fuzzy model can be used to analyze, simulate, and test the influence of parameters and predict the behavior of the system. FCMs have gained considerable research interest over the last decade and have been used in modelling a large variety of systems [26]–[29]. A FCM can be represented by a 4-tuple *(C, W, A, f)*, for intervals of K = [-1 1] and L = [0 1], described as follows [30].

$C = \{C1, C2, ..., C_n\}$ is the group of n FCM concepts. $W: (C_i, C_j) \rightarrow W_{ij}$ represents a causal relation (weight) connecting input and output concepts. Respectively, $W_{ij}<0$ and $W_{ij}>0$ indicate a negative and positive causal relationship. $\|W_{ij}\|$ is the intensity of the causal relationship. Finally, $W(CxC) = W_{i,j} \in K^{nxn}$ is the connection matrix. $A: C_i \rightarrow A_i$ is the degree of activation of a concept (1). $A(0)$ is the initial vector, that specifies the values of all concept nodes, and $A(t) \in L^n$ is a state vector in iteration t. $f(x): R \rightarrow L_i$ is a decision (sigmoid) function (2), which includes the recurrent relationship at $t \geq 0$ between $A^{(t+1)}$ and $A^{(t)}$. λ is a positive number that indicates the learning rate, or the sensibility to the changes of A (λ=1 in this work).

$$A^{(t+1)} = f\left(\sum_{j=1}^{n} W_{ij} \, . \, A_j{}^t\right) \tag{3}$$

$$f(x) = \frac{1}{1+e^{-\lambda x}} \tag{4}$$

The proposed FCM is called DFCM since it modifies/updates its weight matrix according to the sensors data and the system actual sub-behavior. In this sense, there is a weight matrix for every sub-behavior, i.e., the DFCM is event-driven by the actual state of the sensors, similarly as seen in [31].

The DFCM-ACO is shown in Fig. 2, in which the diamonds correspond to the decision-making process. The authors tuned these causality levels empirically according to the simulation results and desired behaviors. The DFCM-ACO's weight matrix is modified/updated according to the events described in Table I and Fig. 1. The event occurrence defines each robot sub-behaviors'. The relation between weights and sub-behaviors are shown in Table II. The weights *W77* and *W88* of sub-behavior 1 correspond to the acceleration of the robots in straight line.

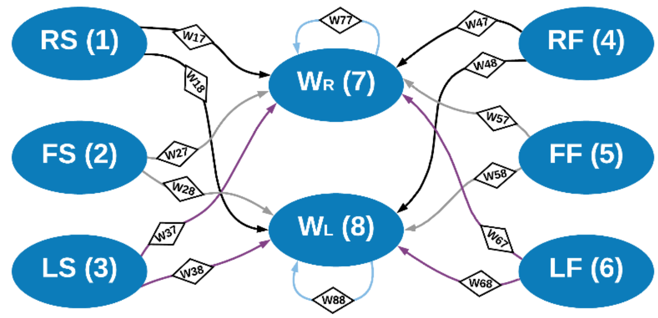

Fig. 2. Proposed DFCM-ACO.

TABLE II. SUB-BEHAVIORS' WEIGHTS

Weight	Sub-behavior			
	1	*2*	*3*	*4*
W17	0.60	0.60	0.80	-0.40
W18	-0.40	-0.40	-0.60	0.50
W27	-0.30	-0.30	-0.80	0.30
W28	-0.30	-0.30	-0.80	0.30
W37	-0.20	-0.20	0.60	0.50
W38	0.20	0.20	-0.40	-0.40
W47	0.80	0.80	0.20	0.00
W48	-0.20	-0.20	-0.20	0.00
W57	-0.50	-0.50	-0.20	0.00
W58	-0.50	-0.50	-0.20	0.00
W67	-0.20	-0.20	-0.20	0.00
W68	0.20	0.20	0.20	0.00
W77	0.10	0.00	0.00	0.00
W88	0.10	0.00	0.00	0.00

In a similar approach as seen in State FCMs [28], the DFCM-ACO has input and output concepts. The inputs are the sensors' data, and the outputs are the pulses sent to the DC motors. However, in oppose to the State FCMs who got state concepts, the DFCM here has state weights, i.e., a different weight matrix according to the robot sub-behavior. Other scenarios can benefit from DFCM-ACO, such as autonomous fertilizer robots, and UAVs for mapping conflict areas. With the addition of ACO in a DFCM, these systems can operate for longer periods and in a more optimally, thus aiming at saving operating resources, such as fuel or batteries, and agricultural inputs.

IV. RESULTS AND DISCUSSION

In this section, the authors show the results from all approaches, but focusing on the DFCM-ACO. The MRS was simulated in each environment using 8 robots. The robots leave a landmark at every 10 iterations to compose its movements/pheromone trails. Thus, the simulated experiments are delimited in 10000 cm^2. However, these dimensions can be readjusted for changes in actual victim search scenarios. In all environments there are six victims in the coordinates (10 40), (10 90), (40 20), (50 80), (90 20) and (90 80) [10]. The initial poses of the robots are given by Table III.

TABLE III. INITIAL POSES

Robot	X (cm)	Y (cm)	Angle (°)	Color
1	15	5	90	Blue
2	25	5	90	Green
3	35	5	90	Red
4	45	5	90	Cyan
5	55	5	90	Magenta
6	65	5	90	Yellow
7	75	5	90	Black
8	85	5	90	Blue

The results of the first environment are depicted in Figs. 3, 4, and 5. For the second one, the results are shown in Figs. 6, 7, and 8. Finally, the third environment generated the results as seen in Figs. 9, 10, and 11, respectively for exploration, covered area, and pulses sent to wheels.

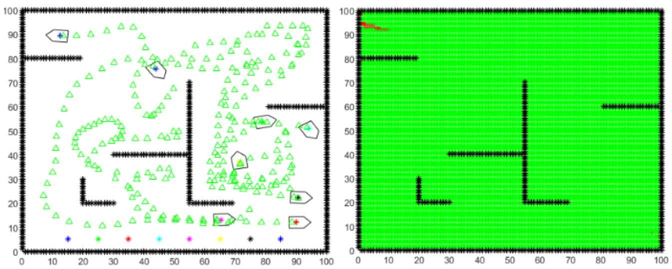

Fig. 3. Environment I exploration and total explored area.

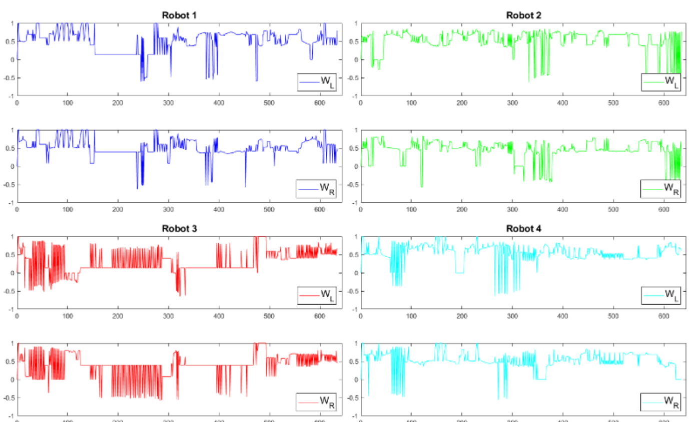

Fig. 4. Pulses for environment I: robots 1-4.

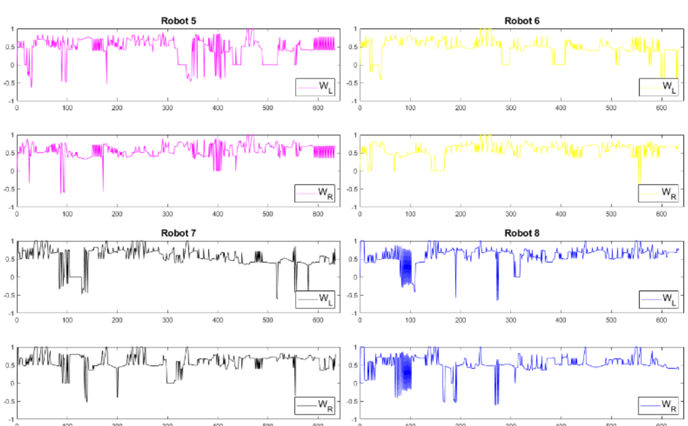

Fig. 5. Pulses for environment I: robots 5-8.

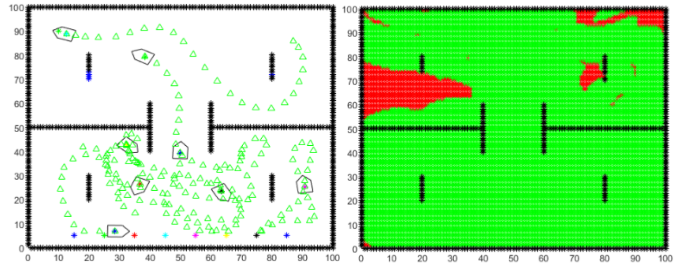

Fig. 6. Environment II exploration and total explored area.

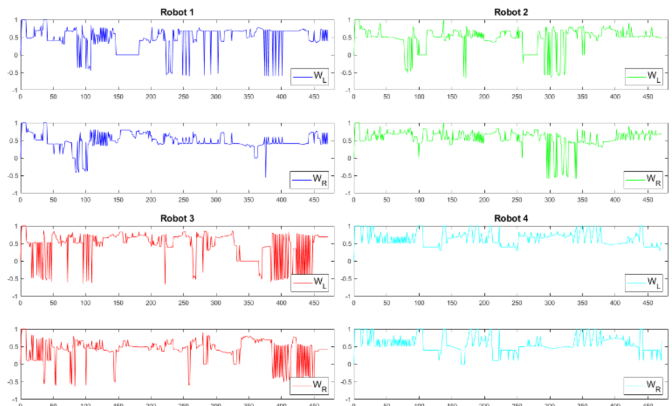

Fig. 7. Pulses for environment II: robots 1-4.

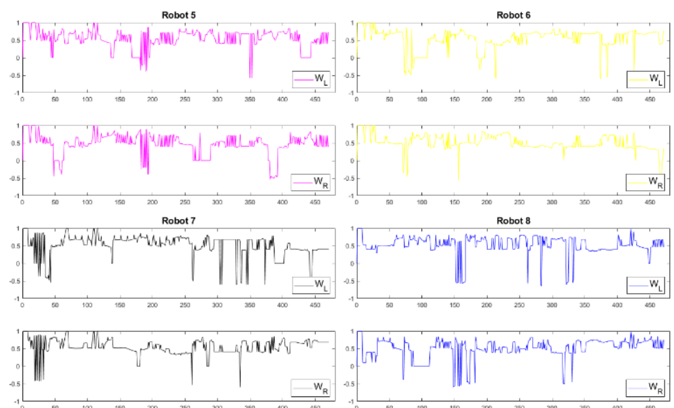

Fig. 8. Pulses for environment II: robots 5-8.

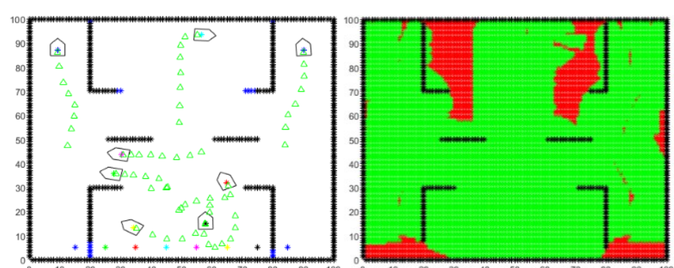

Fig. 9. Environment III exploration and total explored area.

The proximity between robots – caused by the size of the environments and the number of robots – triggered the sub-behavior of imminent collision, e.g., as seen in Figs. 4 (robot 3 at iteration 200), 7 (robot 2 at iteration 300), and 11 (robot 7 at iteration 20).

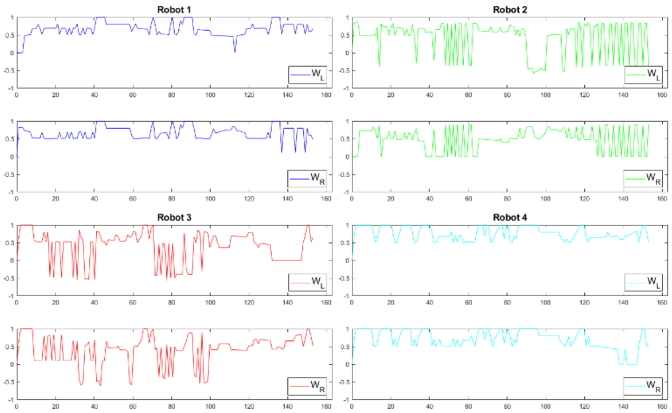

Fig. 10. Pulses for environment III: robots 1-4.

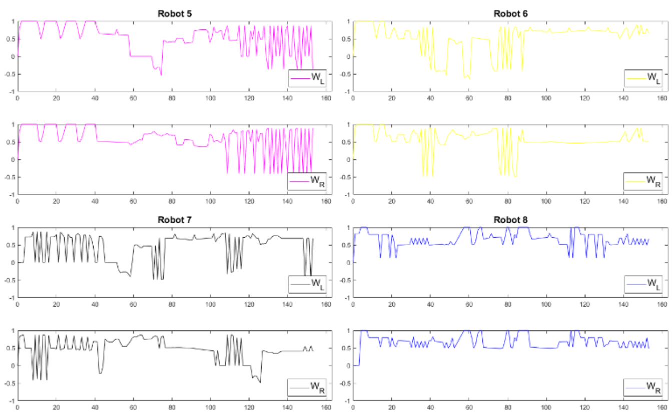

Fig. 11. Pulses for environment III: robots 5-8.

TABLE IV. EXECUTION TIME AND NUMBER OF ITERATIONS

Controller	FLC	DFCM	DFCM-ACO
Environment I			
Time (s)	1204.04	647.99	739.94
Iterations	355.00	400.00	634.00
Environment II			
Time (s)	976.84	493.59	621.39
Iterations	435.00	283.00	471.00
Environment III			
Time (s)	487.63	297.41	240.46
Iterations	155.00	162.00	153.00

The DFCM approach completed the task with less iterations only in the second environment. However, as seen in Table IV, in all environments the proposed strategy consumed less processing time. This feature suggests that, with the increase in the number of robots, the DFCM approach will continue to consume less computing power to be implemented without prejudice in the battery life, as seen by the number of iterations. In the case of the DFCM-ACO, its results suggest a balance between explored area/traveled distance and the processing time, as seen in Tables V to X.

The results presented in Tables V, VII, and IX, the DFCM and DFCM-ACO robots traveled less in all scenarios expect the DFCM-ACO in the first environment, i.e. even presenting similar total explored area, suggesting again an extended battery autonomy in real-life.

From the analysis of Tables VI, VIII and X, the robots explored at least 85% of the proposed environments. This fact, combined with the identification and rescue of all victims, represents that the robots completed their task with an area dispersion within expectations, a fact stimulated by the released repulsive pheromones, as seen in Figs. 3, 6 and 9.

TABLE V. TRAVELED DISTANCE (CM): ENVIRONMENT I

Robot	FLC	DFCM	DFCM-ACO
1	211.53	218.72	269.81
2	198.22	214.95	255.35
3	237.75	190.93	188.91
4	150.93	192.45	282.97
5	208.54	183.22	271.36
6	198.37	161.22	281.13
7	231.70	197.37	299.89
8	191.13	197.48	298.65
Total	1628.16	1556.34	1849.42

TABLE VI. EXPLORED AREA (CM^2): ENVIRONMENT I

Robot	FLC	DFCM	DFCM-ACO
1	3937.00	4574.00	4841.00
2	3737.00	5146.00	5878.00
3	4830.00	4083.00	3668.00
4	3884.00	4556.00	6507.00
5	3535.00	4249.00	4740.00
6	3765.00	3855.00	3898.00
7	4460.00	4059.00	4169.00
8	4109.00	3517.00	6093.00
Total	9757.00	9840.00	9973.00

TABLE VII. TRAVELED DISTANCE (CM): ENVIRONMENT II

Robot	FLC	DFCM	DFCM-ACO
1	222.87	113.71	189.07
2	257.74	111.95	206.44
3	210.65	118.89	166.61
4	272.00	148.19	242.76
5	212.78	129.99	200.50
6	237.39	145.18	206.72
7	212.61	116.56	210.14
8	200.31	137.76	202.51
Total	1826.35	1022.23	1624.75

TABLE VIII. EXPLORED AREA (CM^2): ENVIRONMENT II

Robot	FLC	DFCM	DFCM-ACO
1	3352.00	1877.00	3745.00
2	2990.00	2774.00	4656.00
3	3282.00	2793.00	3183.00
4	4896.00	3739.00	5055.00
5	2850.00	3520.00	2793.00
6	4886.00	3152.00	3777.00
7	3046.00	3135.00	3970.00
8	2287.00	3059.00	4210.00
Total	9475.00	8896.00	9174.00

The three MRS approaches showed similar results in relation to the covered area, as can be seen in Tables VI, VIII, and X. Thus, the ratio between processing time and explored area of the DFCM-MRS is significantly higher than the FLC-MRS, e.g. in environment I, where this ratio is almost the double. In addition, the unexplored regions could be covered if the authors used another stopping criterion in the simulations, e.g. time.

TABLE IX. TRAVELED DISTANCE (CM): ENVIRONMENT III

Robot	FLC	DFCM	DFCM-ACO
1	85.36	86.90	84.55
2	100.90	46.07	56.88
3	76.81	83.89	51.28
4	93.02	72.06	93.87
5	104.08	96.85	70.88
6	94.07	62.69	69.74
7	73.01	61.47	58.12
8	86.88	89.38	85.21
Total	714.13	599.31	570.53

TABLE X. EXPLORED AREA (CM^2): ENVIRONMENT III

Robot	FLC	DFCM	DFCM-ACO
1	2157.00	2280.00	2189.00
2	2541.00	1310.00	1573.00
3	1860.00	2348.00	1579.00
4	2518.00	2240.00	2510.00
5	2824.00	2622.00	2087.00
6	2224.00	1641.00	1850.00
7	2013.00	1746.00	1421.00
8	2069.00	2293.00	2273.00
Total	8994.00	8787.00	8557.00

Figure 12 presents an overview of the processing times of FLC, DFCM, and DFCM-ACO controllers in the proposed MRS. Considering the tested scenarios, the DFCM and DFCM-ACO strategies consumed less processing time than the FLC in all environments. However, when comparing both DFCM strategies, the DFCM-ACO simulations lasted more in environments I and II.

Respectively, the performance difference between FLC (slower in all scenarios), DFCM and DFCM-ACO is 85.81% and 62.72% in environment I. In the second one, the difference between FLC and DFCM is at about 98%, and 57,20% between FLC and DFCM-ACO. The third environment was the fastest one, with difference between FLC, DFCM and DFCM-ACO respectively 63,96%, and 102%.

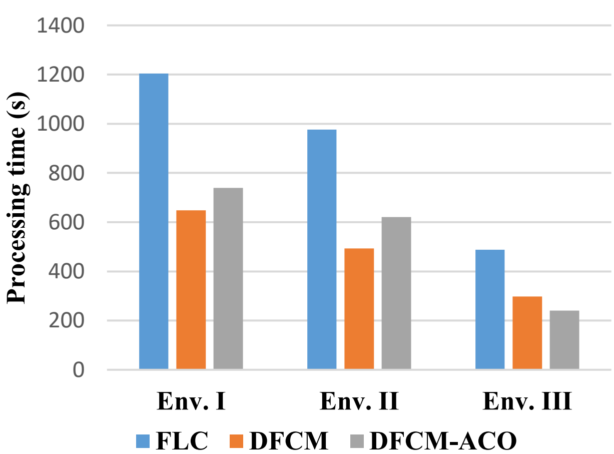

Fig. 12. Graphical comparison of the MRS approaches.

V. CONCLUSIONS

The observed results showed flexibility in the communication between the robots and the autonomy in the exploration and rescue of the victims. These aspects suggest that the DFCM control can be successfully used in autonomous robots, since this controller presented optimized results compared to FLC. The DFCM-ACO approach presented a better balance between explored area and processing time in comparison to the other ones.

The DFCM-ACO MRS rescued all victims while traveling larger distances than the DFCM, but consuming less processing time than the FLC and presenting explored area values located between FLC and DFCM. The employment of this strategy met the expectations by expanding the DFCM explored area, resulting in less battery consumption in real-life applications.

As a result, the computational performance of the DFCM approaches, consisting of the number of iterations and processing time, has a clear advantage in these eight robot scenarios, due to its improved scalability compared to FLC. Therefore, it is concluded that the results meet the objectives set initially, since they are able to act autonomously in different environments, capture their targets and avoid obstacles. Furthermore, it is noteworthy that the use of DFCM-based strategies can be beneficial for low cost financial applications, such as the Arduino platform, which have low processing power.

An objective for future work is the implementation of a larger group of robots and different scenarios, as well as validation through experiments with a prototype. In addition, simulations looking for emerging behaviors in robots and testing the possibility of failure to verify the robustness of the group. Finally, the addition of collaborative behaviors and the use of the leader concept for the robot group (guided by the users or not) will be studied.

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