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RESEARCH ARTICLE

Collective Mapping of Gas Leakages to Determine Safe Routes Using Multi-Robot System

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ABSTRACT This article discusses a novel approach to collective mapping that uses autonomous sensors to create safe routes in environments with gas leaks. Multiple mobile sensors seek to delimit different regions and assign them different tasks according to their momentary needs. In this study, robot groups act as multiple composite sensors that can move independently according to their assigned functions. Autonomous detection, collective mapping, and collective decision-making of the robots are behaviors bioinspired by the cognitive mechanisms observed in bacterial colonies. These colonies continuously seek to maintain the lives of their species based on their collective decision-making in searching for energy sources and changing colony size. In addition, as gas dispersion in the environment increases, the received data from the sensors aids collective decision-making, assigning different functions, such as mapping, environment exploration, and route creation, to groups of mobile sensors. Depending on the momentary need, the number of sensors in each group changes. The proposed method in this study was based on real mobile robots with characteristics that enable varying levels of scalability in size. Subsequently, it was evaluated in a simulated system and developed for experimentation with gas and mobile sensors in a dynamic and realistic environment. This study further contributes to analyzing multiple tasks in homogeneous sensor groups executing different tasks. Furthermore, this work introduced a simulated experimental system to test different topologies of multiple scalable mobile sensors.

INDEX TERMS Gas mapping, safe route, multiple mobile sensor, scalable size.

I. INTRODUCTION

One characteristic of industrial processes is the use of complex systems composed of potentially dangerous gases, which can affect the physical integrity of the environment and the health of the people who work there. The gases that make up industrial systems have physical, chemical, and biological characteristics that can cause severe injuries when in contact with the skin or even inhaled. In addition, many of them are explosive. The context of this study is based on the need to improve the monitoring of these gases in industrial environments, where failures can lead to high-risk situations.

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An important characteristic of these gases is their distribution dynamics. This is because parameters such as temperature, pressure, wind speed, and humidity can directly influence the behavior of these gases. The motivation for this work is that, despite existing monitoring systems, gas leaks are inevitable, and there is a demand for more dynamic solutions to deal with these incidents. Therefore, in indoor industrial environments, it is vital to continuously monitor the possible sources of gas leaks to avoid the aggravation of undesirable situations, such as intoxication. The central problem addressed in this study is the limitation of the current fixed sensors, which restrict monitoring to specific points, leaving some areas uncovered. Despite this, gas leaks occur inevitably. Thus, gas mapping of fully functional industrial plants is paramount. To address this

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issue, this work proposes the use of mobile sensors, which allow for wider and more precise mapping, as well as the identification of leak sources. It is possible to monitor the dynamics of gases by using gas maps to prevent unwanted gas leakage. Furthermore, gas mapping helps identify safe routes for evacuating people during a gas leak.

Currently, most industries use fixed sensors to monitor possible gas leaks.

However, this approach limits monitoring to the points where the sensors are installed. The main contribution of this study is the introduction of mobile sensors, which, unlike fixed sensors, offer greater versatility and coverage of industrial areas.

One way to cover larger areas and perform more extensive gas detection is by using mobile sensors. The versatility of systems with mobile sensors provides a series of alternatives that can benefit the industrial sector, such as dynamic gas mapping, gas source identification, and active exploration and gas detection. In this context of monitoring, mobile sensors of scalable size can be used to reach restricted areas due to their size and allow an increase in the accuracy of measurements. In addition to mitigating the issues involved with gas mapping, this study presents solutions that assist in resolving problems after a gas leak is detected. The limitations faced include the complexity of the mobile sensor system, which requires continuous coordination between devices to ensure a quick and efficient response.

Thus, safe routes that can be used during evacuation and maintenance have been proposed because gas leaks in the industry must be contained quickly to avoid possible contingencies, such as explosions and intoxication.

This article is structured as follows: Section II addresses related work and the challenges that need to be overcome. Section III explores the theoretical approach and experimental development. Section IV describes the methodology adopted and the experimental configurations used. Finally, Section V discusses the results obtained and points out the conclusions and future directions.

II. RELATED WORKS

The possibility of gas leakage is inherent in industrial environments. Thus, developing systems and techniques capable of mapping gas dispersion and minimizing risks to people and the industry are highly relevant. There are several ways to perform gas mapping. For instance, stigmergy-based methods [1] and Bayesian-based motion planning algorithms [2] have been explored, demonstrating effectiveness in different gas mapping scenarios, but with varying infrastructure requirements.

In the study, a set of simulation studies were conducted to compare the performance of uncoordinated and coordinated algorithms. Different initial conditions and robot sizes were also considered. The simulation and experimental results showed that the algorithm that involved coordination surpassed traditional bioinspired source seeking (SS) algorithms, and between 1 and 8 robots were used for analyzing these algorithms. Simulation studies showed that coordinated algorithms outperform traditional bioinspired SS algorithms, with performance improving as the number of robots increases.

A collaborative mobile sensing algorithm [3] was used to build scalar field maps, but results were limited to theoretical models without considering scalability or communication intervals. Thus, a control law built into robots was proposed to avoid robot collisions during displacement.

Knowing whether gas mapping is related to obtaining basic information about how a gas disperses in an environment is also important. This was explored in reference [4]. From the study, It was observed that it was difficult to consider it an obstacle in the field of mobile robotic smell (MRO), as it impairs the ability to validate strategies to build gas distribution maps produced by autonomous mobile robots. Reference [4] explored gas mapping using fixed sensors, but sensor passivity introduced delays, highlighting the need for mobile robotic systems to improve detection efficiency.

When mobile robots are used to explore and monitor the gas distribution in an environment, it is possible to list different forms of the subject. One way of doing this is to categorize the forms into active strategies where the robots follow a predefined strategy, whether it be exploiting the same trajectory or adaptive, as proposed in [5], and where different measures are available to ensure their actions are taken into account according to the perceived need. In [5], robots followed predefined or adaptive strategies for gas distribution mapping, with proactive strategies ensuring better area coverage compared to passive methods.

However, this kind of approach may be insufficient in overcoming all the gas dynamics problems. Therefore, this present study proposes an alternative approach that uses multiple mobile robot groups to ensure total coverage of the simultaneous needs in this field. Furthermore, the alternative approach to address the need for gas detection, presented in [6], proposed the use of unmanned aerial vehicles (UAVs). These devices have promising characteristics for mapping and detecting gas owing to their ability to inspect and access difficult areas without exposing the operator to risks. In the study [6], a coordinated swarm of UAVs were equipped with gas sensors to monitor industrial air pollution. However, this approach was conducted in outdoor environments with considerable space for robot navigation. Realistically, several industrial environments are small and confined. Therefore, the approaches presented subsequently provide solutions for industrial environments with characteristics that do not allow the use of UAVs. While these UAV swarms proved effective in large outdoor areas, this approach faces limitations in confined industrial environments, which the present study addresses by proposing a solution involving mobile ground robots. This article proposes gas source locating, dynamic trajectories planning, and delimitation of safe routes in a gas environment. Numerous approaches are being studied to circumvent gas source location problems, such as obstacles and turbulent airflows. In [7], a probabilistic solution using a terrestrial mobile robot that revolves around the spread of local estimates throughout the environment was presented. This propagation explored the environment and assumed controlled environmental conditions, thus avoiding analytical dispersion models.

The constant need to increase people's safety drives the development of gas leak control technologies in several sectors. Concerns regarding suspended gas particles in the air are significant, and this is particularly inherent in industrial environments. Owing to this, an Internet of Things (IoT) system connected to several gas sensors that continuously provided estimates and information on air pollution and air quality was developed in [8]. The study highlighted the need to monitor air quality for the benefit of human health. In addition, the creation of safer routes for the maintenance of gas systems and evacuation of places at risk is emphasized in reference [9], in which rescue maps are developed using different technologies, including a combination of bluetooth sensors, firefighting equipment, global positioning systems data, optimal fire rescue route planning algorithm, and visual technology. The study results showed that it is possible to build dynamic rescue and evacuation procedures for firefighters, but this work does not provide solutions for analysis and coverage of the location where hazardous situations occur. By providing real-time updates for optimal path planning, the information becomes more accurate for firefighters, decreasing the number of victims. An alternative to adding robustness to the creation of safe routes, whether used for escape or maintenance, is through mobile sensors, which can adapt to different environments and detect air pollutants and provide information that can assist in making informed decisions regarding, for example, safe evacuations and repairs.

Some studies have shown the dynamic behavior exhibited by gases, which undermines actions carried out with fixed sensors, as in [4], where a platform to map the gas distribution and gas leak location using a 3D metal oxide sensors (MOX) grid was presented. However, the measurement point was static, which made it applicable only to local data. In [10], a novel collective sensing approach was proposed using autonomous sensors designed to monitor gas leaks and find gas sources. One of the objectives of the study [10] was to better verify results through a collective search for gas sources. However, in this present study, multiple sensors act as composite sensors that can move independently to find an ideal detection zone. Although this work has had a detailed and criticized analysis in several aspects, gas mapping and safe escape routes creation have not been explored. Therefore, these gaps need further exploration.

The systematic approach to using mobile robotics for environment navigation and exploration leverages potential fields where gas concentration can be considered the source of the potential field. This technique has been widely employed for mobile robot navigation, as demonstrated in [11], where an enhanced artificial potential field (E-APF) was used to generate executable trajectories for mobile robots. This approach also aims to solve the gap perceived in the classic artificial potential field (APF), which refers to the difficulty in adapting to trajectory planning and falling into a solution with an excellent location. Therefore, the E-APF method is proposed for planning routes for wheel-mounted mobile robots (WMR). Reference [12] also reported the use of potential fields to control the formation of multiple robots due to their simplicity and efficiency in dynamic environments. However, an adjustment of the fuzzy inference in the potential field parameters was proposed to overcome the limitations of the APF technique. Another general approach in the area of multiple robots is the collaborative task performance between robots, as presented in [13], the transportation of an elastic plate in an unknown environment was investigated using a group of small swarm mobile robots (SMR). An improved potential artificial field method was used to plan the routes and the formation control of the mobile robots. These studies express some of the potential field technique capabilities in scenarios involving multiple mobile robots. The map generated from the mobile sensors was used in the [14] work for the component responsible for the interaction of the robots with the gas. To reconstruct the gas distribution and estimate its gradient for potential field construction, a 3D weighted regression strategy was employed. This approach enables accurate gradient estimation, which is crucial for building reliable potential fields. An additional point that could be explored is integrating real-time sensor data to dynamically update the gas map, enhancing the system's adaptability to changing environmental conditions.

The search for solutions to complex problems of human civilization came through the observation of nature, that is, solutions were inspired by how different species solved their problems. Human beings adapted their solutions, as is, for example, the case in [15], where the results of the understanding of the olfactory search in flies and rodents are presented. As *chemotaxis* (observed in bacteria and other microorganisms, as a constant search behavior for energy sources) is relatively well understood, olfactory search algorithms and mechanisms need further development in larger animals. Another essential fact reported in [16] refers to the use of mobile robots in locating sources in aggressive environments, such as in a poisonous atmosphere or underwater, to perform tasks better than animals without being hurt. Other search algorithms, such as bioinspired ones based on gradients, multi-robots, probabilistic, and base maps are presented in this article. The solution proposed in this study is bioinspired and draws upon the cognitive mechanisms observed in bacterial colonies. It involves their remarkable abilities, such as detecting energy sources, transferring information between colony members, making collective decisions, restructuring group capacity, and leveraging the physical characteristics unique to these small beings, including their size and locomotion. These characteristics are essential for the miniaturization of robots.

Thus, the work presented in [17] unites several essential points in mapping using multiple robots. Considering map construction generally assumes that the robot positions are unknown, thus requiring an estimate during the execution of tasks, it goes against a branch of robotics widely studied and known as simultaneous location and mapping (SLAM). However, the use of multiple robots that involve localization and mapping requires a wide area of research. The association between these concepts and gas mapping offers this work the opportunity to propose alternatives in using multiple mobile robots to perform gas mapping in an integrated way in indoor environments and provide information on safe routes. Adaptability to the environment, which increases and decreases the groups of robots without altering the execution of the task, is a benefit observed in this solution.

III. COGNITIVE AND COLLECTIVE MAPPING

This section presents solutions for gas detection using multi-robot systems to assist in gas source detection, gas mapping, and the creation of safe routes in indoor environments with gas leaks. The versatility of multi-robot systems provides a series of alternatives that can benefit different sectors in activities, such as dynamic gas mapping, gas source location, active environment exploration and gas detection, exploration of unknown environments, collaborative work in industrial processes, and logistics. Thus, a bioinspired approach is presented to develop efficient solutions for these problems. The approaches presented in this section differ in their dynamics. One of the approaches introduced an autonomous search behavior carried out through gas measurements. As the dispersion of gas in the environment increases, the gathered data assisted in collective decision-making, assigning different functions, such as mapping, exploration, and creating safe routes, to the dynamic groups of SMRs.

Depending on the momentary need, the number of robots that comprise these groups can be changed. The method subsequently proposed in this study was evaluated in a simulated system and developed for experimentation with gases and mobile sensors in a dynamic and realistic environment. Several experiments were designed to elucidate the collective contributions of mapping and creating safe routes in environments subject to gas leakage. Furthermore, this study contributes to the analysis of multiple tasks in homogeneous groups. A simulated experimental system was developed to test the different topologies of multi-robot systems. This study discussed a new approach to collective mapping using autonomous sensors to create safe routes in environments with gas leaks. A multi-robot system seeks to delimit different regions, assigning them different tasks according to a momentary need. The collective approach seeks to optimize the routes to the gas source, offering safer alternatives for accessing the environment. The sharing of information between robots is essential to ensure that the mapping and safe routes are balanced in terms of the different functions of mobile robots.

In this study, robot groups act as multiple composite sensors that can move independently according to the function assigned to them. Furthermore, autonomous detection, collective mapping, collective decision-making, and memory inheritance behaviors of the robots were bioinspired by the cognitive mechanisms observed in bacterial colonies that continuously seek to maintain the life of their species based on their collective decision-making in searching for energy sources and varying colony size and task assignments.

A. THE GAS DETECTION PROBLEM

An inherent characteristic of most industrial, commercial, and residential environments is the possible exposure to gases that have adverse effects on human health through intoxication or exposure to the explosive properties that these chemical and biological agents can present. A striking feature of these gases is their dispersion dynamics, since parameters such as temperature, pressure, wind speed, and air humidity, among others, can directly influence the behavior of gas dispersion. In indoor environments, the monitoring of possible gas leaks must be carried out continuously to avoid the aggravation of dangerous situations. Therefore, gas mapping is of utmost importance. It is possible to verify and monitor the dynamics of gases, making it possible to solve problems such as unwanted gas leakage. In gas source identification and leak detection, the approach presented so far is insufficient in offering a complete solution capable of providing relevant information on the environmental risks associated with a gas leak. Thus, gas mapping brings data sets that make it possible to enhance the approach and create safe routes in an environment exposed to harmful gaseous agents. Figure 1 presents an overview of the issues addressed in this section.

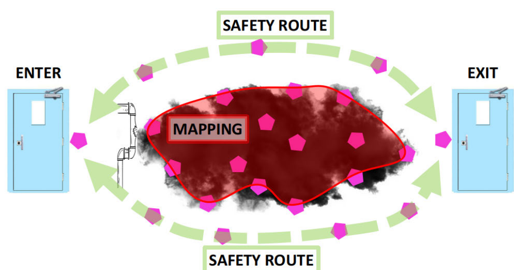

FIGURE 1. An overview of the gas mapping and safety routes generated from measurements made using the mobile robots represented by the magenta pentagons.

A collective and bioinspired approach involving a multi-robot system, gas mapping, and multiple tasks is a solution. One of the fundamental issues with this approach is that all robots that make up the system need to be continuously available for efficient decision-making. Exploring environments involves several concepts that can be approached in different ways. In this section, mapping-related limitations, such as different levels of collective memory and variations in the number of samples across systems with different scalability, are addressed using potential field techniques to assist in developing the proposed solutions in the objectives of this work. Thus, a joint solution with multi-robot systems can integrate gas mapping, gas source location, and safe route delimitation. The cognitive mechanisms observed in bacteria are also a source of inspiration for determining the behavior of the SMR in this study. However, to assign more integrated functions to SMRs, a more complex approach is required that involves new cognitive mechanisms. Therefore, in addition to the *quorum sensor*, *chemotaxis*, *sporulation*, and *conjugation* behaviors were added. Although the approaches involve information transfer, collective memory, and joint decision-making, no learning method is presented in the proposed solutions.

B. COLLECTIVE MAPPING

In this study, the integration between different areas of science was fundamental for developing the collective gas mapping using mobile robots integrated with the concepts of potential fields. Each robot that detects gas level influences the composition and direction of the generated potential field. Therefore, the information needed to compose a gas map is related to the number of samples collected. Furthermore, storing historical measurement information in the gas detection process can influence the generated map. As the data increases, the mapping becomes more complex due to the volume of information available for decision-making.

Therefore, the greater the number of robots or the more significant the collective memory capacity, the more refined the mapping performed. However, some limitations in system scalability need to be verified, as there are limits where information saturation occurs, as observed in [10]. Thus, the potential field approach aims to present different information, such as the range of saturation in the number of robots in an SMR. Over the years, hypotheses have been raised that collective behavior improves the different tasks performed in the animal world. In this work, bioinspired behaviors in the cognitive mechanisms of bacteria were explored to perform different tasks efficiently.

Classical techniques focused on collective behaviors assume that social organizations benefit from the grouping of imperfect estimates, either by the average or by the vote of agents belonging to the group, which is evaluated as the group size increases. When this phenomenon is considered for collective detection, some specific characteristics can be noticed in an environment full of uncertainty and noise. For example, in a gas-immersed environment, it is possible to check, through several measuring points, different values for gas concentration gradients. After analyzing these measurements, it can be concluded that if each individual makes its own local and imperfect estimate of the direction of the gradient and, later, gathers this information through the clustering trend, this detection capacity can be improved, as presented in [18]. An expression that portrays this is known as the *wisdom of crowds*.

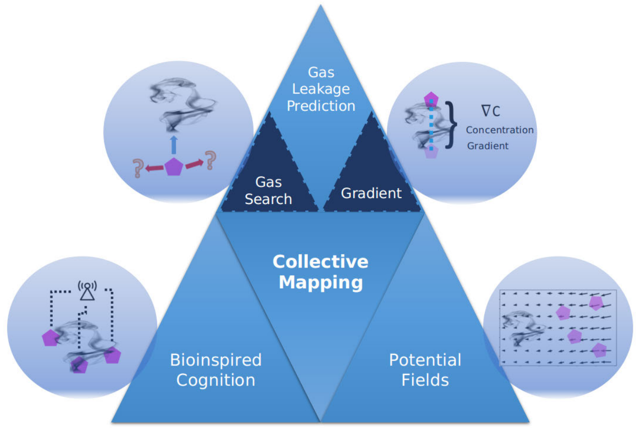

FIGURE 2. Representation of the proposed approach to collective mapping, integrating the different needs observed in each stage.

The technique for collective mapping proposed in this work presents a cognitive approach with different levels of complexity, thus, generating solutions that can be targeted according to the need and availability of resources, such as the number of robots and the information storage capacity of multi-robot systems. The steps involved in developing the solution presented in this work have an interdependent and direct structure. Figure 2 shows the individual dependencies of each stage and their integration.

C. PREDICTION OF GAS LEAKAGE AND POTENTIAL FIELDS

The realization of a collective bioinspired gas mapping through mobile robots goes through detection and measurement at the gas level at different coordinates and instants, thus, it is possible to calculate the variation of the gas concentration and subsequently its gradient. The technologies involved in these processes are described in this section. The trajectory taken by mobile robots uses the principles of potential fields to determine the navigation directions that each robot should follow, resulting in a point-to-point trajectory. Thus, three main components are evident in the composition of the potential field:

1) collision with other obstacles;
2) gas concentration camp;
3) attraction component.

The field is one of the fundamental characteristics of this technique, which refers to the possibilities of the field that can be directed both toward the growing region (positive chemotaxis) and the decreasing concentration (negative chemotaxis). Chemotaxis refers to the cognitive behavior observed in bacterial colonies, where they tend to move towards regions of higher food concentration, according to the variation in the gradient detected by the colony. Thus, the change takes place due to the exemplary behavior of the robots as they approach the gas source. Furthermore, these three components allow the gas to be mapped in the environment and create safe and dynamic routes. One of the main features of field sampling with mobile robots is unstructured detection because the position of each robot is defined in real-time. Thus, it is challenging to estimate the gradient field using classical numerical gradient calculation methods. An efficient approach to this problem is to estimate the mean gradient, as presented in [19], where the gradient is used in ray-tracing techniques. Another alternative approach is to use regression techniques, as shown in [14], where the gradient is used to render three-dimensional volumes. Some studies on gas mapping show difficulties in developing motion strategies based on gradients, as seen in [20], because the gradient can change very quickly. Therefore, the approach based on weighted linear regression was chosen because it is a well-established gradient estimation strategy that allows the capture of the average behavior of the gas around a point, minimizing difficulties due to the significant variations reported in the article of [20].

The construction of the second generating component of the potential field was obtained by mapping the concentration of gases in the environment. A linear function approximates the gas distribution function around each robot. Consequently, the parameters related to the field growth directions are calculated, allowing the robot to approach or depart from the source according to the desired behavior. Inspired by the three-dimensional rendering in [14], this approach allows the correct analysis of data obtained from mobile robots. Each piece of information is stored in the collective memory of the SMR and is associated with a weight in each regression. The weight stipulated in the data decreases with time and the robot's distance from its previous positions. This technique is performed individually in robots to obtain a local estimate of the function.

Thus, the regression estimates the functions on the x and y components of the space and the t component of time. The weight is presented in Equation (1), which follows the same weight directives proposed in the work of [14], with a quadratic reduction and a change of points with a distance close to zero. The distance between the samples, that is, the robot j, is defined by the Equation (2). The points used for the regression were obtained using mobile robots. The variable A in Equation (3) represents the gradient in question.

$$W_{ij} = 1/(c + d_{ij}^2) \tag{1}$$

$$D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (t_i - t_j)^2} \tag{2}$$

$$B + \begin{pmatrix} x_1 & y_1 & t_1 \\ x_2 & y_2 & t_2 \\ \dots & \dots & \dots \\ x_n & y_n & t_n \end{pmatrix} A = \begin{pmatrix} f_1 \\ f_2 \\ \dots \\ f_n \end{pmatrix} \tag{3}$$

A regression is performed based on Equations (4) - (6). In this study, the approach was slightly modified to allow the regression to be done at points where there are no gas concentration samples.

$$W_{ij} = 1/d_{ij}^2 \tag{4}$$

$$D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{5}$$

$$\begin{pmatrix} (x_1 - x_0) & (y_1 - y_0) & (z_1 - z_0) \\ (x_2 - x_0) & (y_2 - y_0) & (z_2 - z_0) \\ \dots & \dots & \dots \\ (x_n - x_0) & (y_n - y_0) & (z_n - z_0) \end{pmatrix} A = \begin{pmatrix} f_1 - f_0 \\ f_2 - f_0 \\ \dots \\ f_n - f_0 \end{pmatrix} \tag{6}$$

After using the quadratic decay as the basis for the regression, this behavior was changed using the Equation (7). This weight is inspired by the *Gaussian* distribution and has a behavior around the origin close to the Equation (1).

$$W_{ij} = c * exp(-d_{ij}^2/C) \tag{7}$$

These concepts, associated with the cognitive mechanisms of bacterial colonies, allow the potential fields approach that assist multi-robot systems in their movement and collective task performance.

D. BIOINSPIRED COGNITION

The dynamics observed in gas monitoring systems offer research opportunities in several areas. A line of research involving mobile robotics is gas mapping, where the premise is to detect gas dynamics at different moments in time. This study proposes a new approach to this problem. The cognitive bacteriological mechanisms applied to mapping problems correspond to the innovations presented for a bioinspired solution using mobile robotic agents. In these systems, the solutions were bioinspired by bacteria, both in physical and behavioral issues.

Chemotaxis is one of the cognitive mechanisms explored in this study. This mechanism accounts for the attraction behavior of robots toward the "food source" (gas source) and repulsion by "antibiotics" (an undesirable area in the experimental environment). Another cognitive mechanism explored was the sensor quorum. As presented in [21], this mechanism can be summarized as the ability to transmit messages between a colony bacteria through chemical messages, which can control the growth pattern of the colony, where messages can be attractive or repulsive. In line with this concept, a solution is proposed to add complexity and robustness to the method by adding properties presented in potential fields.

Collective decision-making is addressed through the cognitive mechanism of *sporulation*. This approach is based on bacterial formation behavior in which collective and individual needs prevail during the decision-making process. An example of this situation occurs when the environment is devoid of energy sources. At that point, the colony decides whether it is prudent to change its size or formation. Therefore, this decision is imperative. A collective decision is made, the main objective of which is the survival of the bacterial colony. Finally, the last cognitive mechanism explored is *conjugation*, where bacterial transfers of information extracted from the environment occur. This

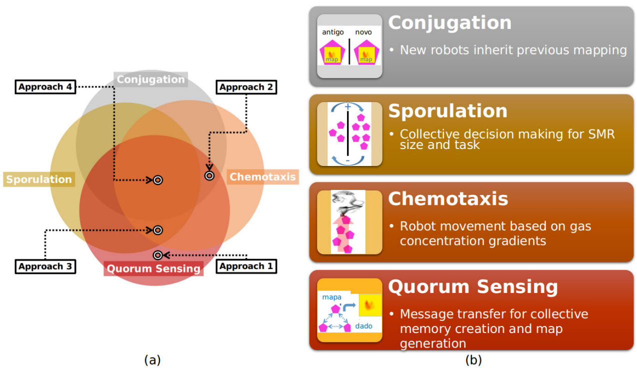

FIGURE 3. (a) Complexity encompassed at each level of cognitive mechanisms. (b) Explanation and relationship between robots and the cognitive mechanisms presented in bacteria.

behavior involves the horizontal transfer of genes, that is, the exchange of knowledge for genes. In this work, this behavior will be addressed by transferring knowledge about the gas map considering a memory with greater storage capacity during mapping and creating safe routes. Combined cognitive mechanisms provide a new approach to collective mapping using a multi-robot system. Figure 3 summarizes the levels of complexity of the bioinspired system.

Thus, experiments will be carried out to consider the characteristics of the cognitive mechanisms of bacteria, together with the theory of potential fields. This approach differs from what has been done so far in lines of research involving gas mapping using multi-robot systems.

IV. EXPERIMENTAL EVALUATION OF COLLECTIVE MAPPING

The experimental environment integrates the GADEN framework and the RVIZ tool. Both are open-source software that can be integrated through ROS, a set of libraries and tools that facilitate the development of robotic applications [22]. The environment was structured according to the GADEN guidelines, as presented in [23]. This package allows specific configurations related to the dimensions of the target environment, selection and number of sensors, temperature, and pressure conditions, among other relevant parameters for the experiments. The sequence of steps to generate the simulated environment is summarized in Figure 4.

To achieve the experimental environment, it is necessary to follow a series of steps. First, the simulation environment must be designed according to the experiment's requirements. Next, a Computational Fluid Dynamics (CFD) simulation is performed to analyze the fluid behavior within the environment. Once this step is complete, the parameters are adjusted as needed to ensure that the simulated conditions accurately reflect the real scenario. The generated database is then fed into the GADEN package to configure the simulated environment. Finally, multiple robots are integrated into the system, enabling interaction and data collection within the

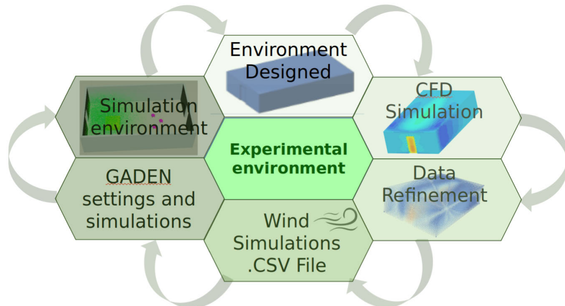

FIGURE 4. Sequence of steps to achieve the simulation environment.

experimental environment in a cohesive manner. While the main details required for experiments are listed in Table 1.

TABLE 1. Gas dispersion parameters.

WIND SIMULATION SETTINGS		
Variable	Information	Unit
Gas	Methane	-
Temperature	298	K
Pressure	10	Atm
Number of sources	1	-
Sensor Model	MOX: TGS2600	-
Turbulence Model	k-epsilon	-
Algorithm	PIMPLE	-
Material	Air	-
Viscosity Model	Newtonian	-
Kinematic Viscosity	1.529e-5	m^2/s
Density	1.196	kg/m^3
Turbulence Kinetic Energy	3.75e-3	m^2/s^2
Dissipation Rate	1.25e-2	m^2/s^2
Wind Speed	0.31	m/s

However, GADEN cannot integrate several mobile robots with the needs established for this study. Thus, it was necessary to develop a system that associates the fixed sensors available in GADEN with the mobility present in an SMR. RVIZ is responsible for integrating the systems available in GADEN and mobility, resulting in a mobile robot capable of continuously measuring and monitoring the presence of gas throughout the experiments. The results for the final environment are shown in Figure 5.

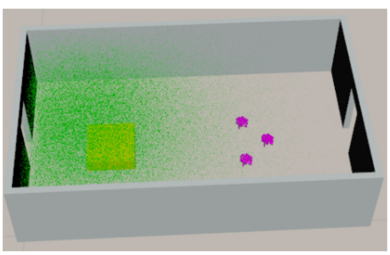

FIGURE 5. Simulation environment generated between GADEN and Rviz.

Mobile robots used for mapping were individually identified in the system using an ID that was used to integrate the virtual sensor with the mobile robot. Thus, it is possible to verify information about the location of robots, allowing for harmonious interaction between them. Various sensor models were used to monitor different types of gases. Thus, they are sensitive to carbon monoxide, methane, ethanol, acetone, and hydrogen. The sensor used in this work was a metal oxide (MOX) semiconductor *TGS2600*.

The chosen method to prove and test the techniques and concepts covered in this work is an experimentation in a simulated environment. Thus, approaches with a gradual increase in complexity were incorporated into the proposed method. First, the collective behavior of the system was tested with the allocation of multiple mobile robots over time to verify the evolution of the gas dynamics. At that time, the robots were kept static. Later, the complexity of the system was increased to provide mobility and assigning tasks to map and locate the gas source. Then, to observe possible gains in system versatility, the behavior of creating safe routes in the environment through instantaneous collective memory was added. Finally, a collective memory with a greater capacity was integrated to perform all tasks reviewed in the experiments: map, search for the gas source, and create safe routes.

One common approach in multi-robot systems is to prevent data duplication when covering the Detection of Alarm Origin (DOA), aiming to ensure efficient coverage and optimize resources. However, this approach is not considered in this work, as the primary goal is to achieve accurate results, regardless of the volume of data, even if it includes duplicated information. This decision is based on the critical safety concerns associated with systems prone to gas leaks, where data redundancy can be crucial to ensuring safety and minimizing potential risks. In this context, accuracy and data reliability take precedence over coverage optimization, ensuring that any indication of danger is detected with maximum certainty.

A. ROBOT WITH SCALABLE CAPABILITY

This work represents a significant evolution and expansion of the research involving the *Monera Robot*, presented by [10]. Building upon its foundation, we have achieved advancements in scalability and miniaturization capabilities. These developments were made possible through exhaustive tests conducted in augmented reality, where it was possible to test and verify the system's response in different tasks, environmental conditions, and control system implementations, as presented in [21] and [24].

The ability to reduce the size of the *Monera Robot* to micro and nanorobotic scales is a notable achievement. Inspired by the cognitive, structural, locomotion, and collective mechanisms of bacteria, we have propelled this miniaturization process. Implementing sophisticated control systems has allowed us to maintain precise and efficient maneuverability, even at these small scales. A notable contribution of this work lies in modeling the robot's movement, as presented at the [25]. We have successfully captured the dynamics and complex behaviors necessary for effective navigation and manipulation tasks through mathematical modeling. This mathematical foundation is crucial in achieving the desired goals of miniaturization. In Figure 6 it is possible to verify the possibilities in the robot size scale in real, cyber-physical, and simulated environments.

FIGURE 6. Robot size scaling possibilities.

The combination of bioinspiration, advanced control systems, and mathematical modeling presented in this study offers a comprehensive solution for the successful miniaturization of the Monera Robot. The implications of this research go beyond robotics, opening up new possibilities in various areas, including healthcare, environmental monitoring, and more.

B. STATIC ANALYSIS OF GAS BEHAVIOR

The less complex experimentation presented in this section was inspired by the *sensor quorum* of the cognitive mechanism presented in Figure 3. Information exchanged between different agents is essential for the composition of the collective memory of this experiment. Understanding gas behavior is fundamental to designing strategies for mapping and searching for the gas source because different concentrations over time can be influenced by bulkheads, wind speed, and atmospheric pressure among other variables. In this scenario, experiments aimed at understanding the dynamics of gas distribution in an indoor environment and mapping the different levels of gas concentration through the exchange of information between robots, consist of placing different numbers of robots (stopped) in random positions in the virtual environment. It should simulate an internal corporate environment. Figure 7 illustrates the arrangement developed for these experiments.

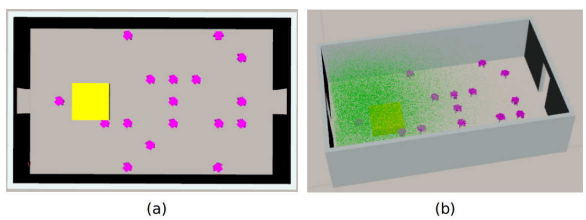

FIGURE 7. Static arrangement of mobile robots to build a map. (a) Superior image of robots distributed in the experimentation environment. (b) Perspective image of robots inserted in the gas environment.

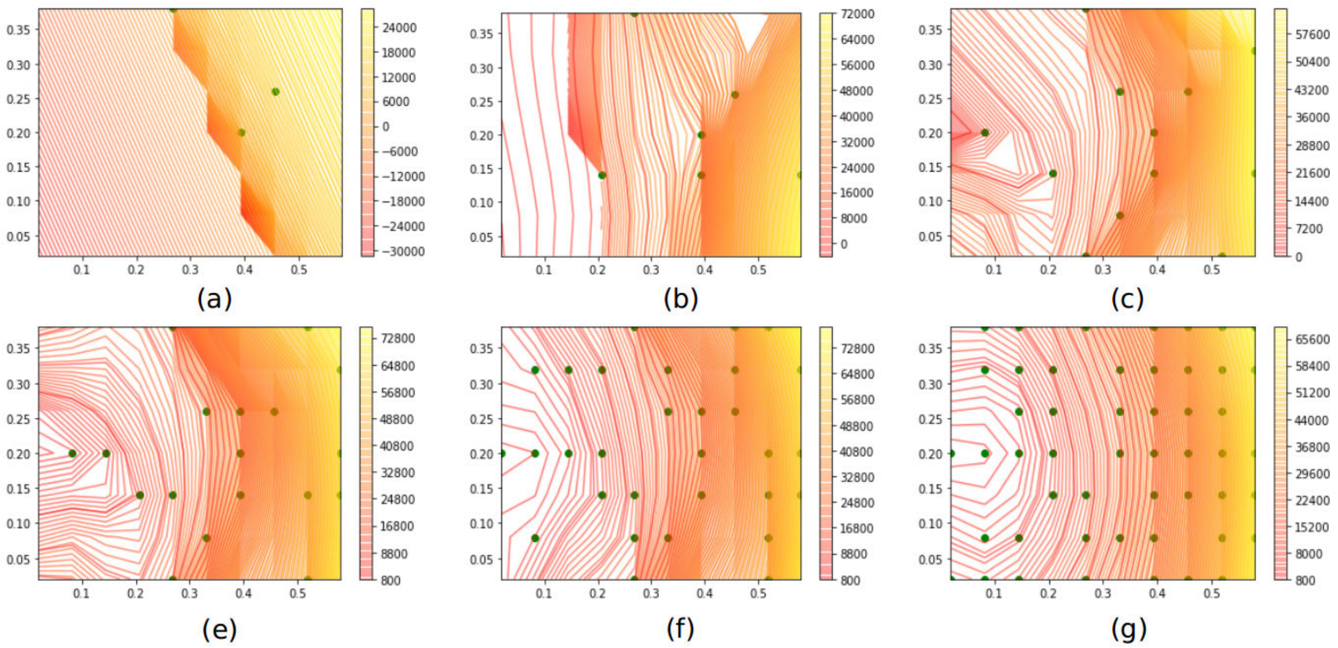

FIGURE 8. Variation in the number of robots for static mapping. (a) Three robots. (b) Six robots. (c) Twelve robots. (d) Eighteen robots. (e) Thirty robots. (f) Fifty robots. Sample at t = 200 seconds and C = 0.01.

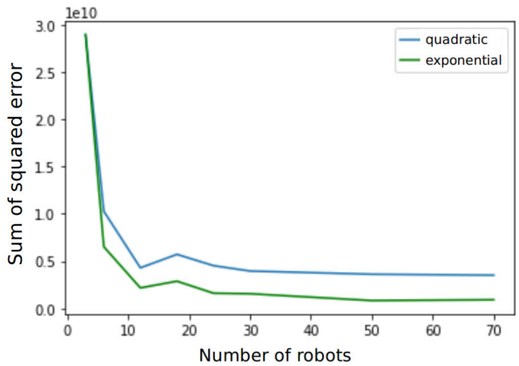

FIGURE 9. Comparison between linear regression weight decay (exponential vs quadratic). Constant C = 0.01.

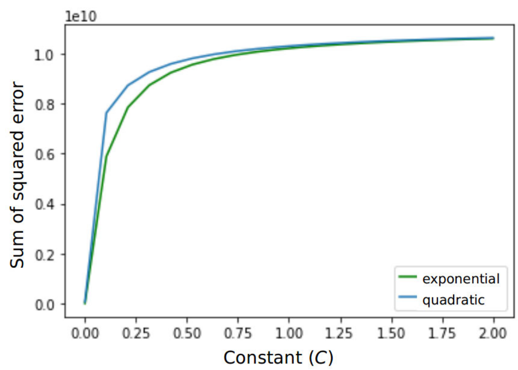

FIGURE 10. Comparison between squared error and the constant C, using 50 statics robots.

This experiment made it possible to perform different gas concentration measurements over time and monitor the dynamics. In this way, different concentrations were noticed, which later helped develop algorithms that express the behavior of multiple mobile robots. In Figure 8, it is possible to observe the difference in gas mapping performed by the variation in the number of robots. The red curve represents the region with the highest gas concentration, closer to the source. As the hue approached yellow, the gas concentration decreased.

The weight used in the regression decay proposed in this solution is exponential. Furthermore, the experiments were also performed using quadratic decay of the regression weights, as proposed in [14]The results of these two approaches are shown in Figure 9. As the number of robots increases to perform gas monitoring, the average error using different decays has a minimal variation of less than 0.5.

The constant C, presented in Equations (1) and (7), verified the influence of distance on linear regression. The results presented in Figure 10 demonstrate that the higher the value of C, the greater the influence of points away from the point of interest.

Furthermore, there was no significant increase in field estimation gain using 30 robots. In this sense, fewer samples can considerably reduce the number of robots and maintain the quality of the concentration estimate. In Figure 10, the comparison of the samples obtained by the total 50 robots and the regression performed is shown. Thus, it was possible to verify that the smaller the influence of samples far from the point of interest, the better the local approximation

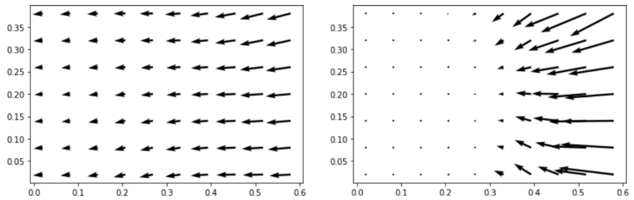

FIGURE 11. **Comparison between squared and exponential gradient estimation, using 50 statics robots and C = 0.01.**

made by the regression. However, the minimal constant C makes storing the distances and weights in floating-point form challenging. Therefore, C was used between 0.001 and 0.2 due to numerical limitations.

Gradient estimation is as important as the analysis of the gas concentration. In this sense, the gradient serves as a guide for robots to move. In Figure 11, it can be verified that despite obtaining better results for field estimation, the regression with exponential weight generates a very discontinuous gradient approximation.

The regression using the quadratic weight presents a gradient that varies more smoothly and allows robots to have a smoother movement. Another fundamental analysis is shown in Figure 12, where different types of gases with different physical characteristics were tested.

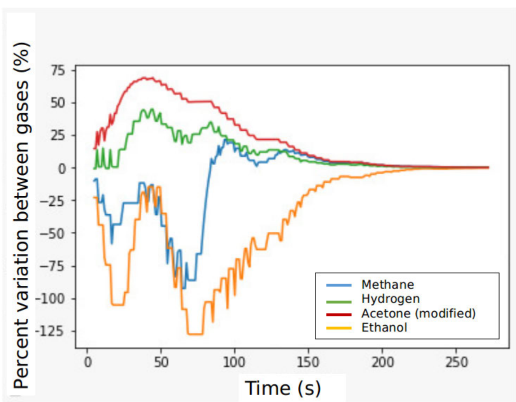

FIGURE 12. **Percent error change during the transient period of different gases.**

During the transient period, each gas behaves differently. Afterwards, the gases entered the stationary regime, and their behavior was similar.

C. CONCENTRATION GRADIENT MAPPING

The mapping approach in this section incorporates an increase in the complexity of the cognitive systems presented in Figure 2. In this type of approach, continuous measurement of the gas concentration is necessary during the robot's movement. Thus, in addition to the *sensor quorum* of the cognitive mechanism, *chemotaxis* was also added, which is responsible for developing the movement behavior of different gas concentration gradients. A multi-robot system was created to perform the task.

In this experiment, mobile robots were randomly distributed in the environment, and the movement was initiated by searching for the highest gas concentration. Therefore, it was possible to dynamically map the gas distribution, as shown in Figure 13.

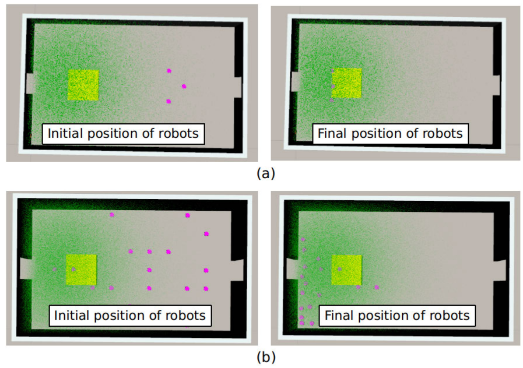

FIGURE 13. **Topology of experiments performed involving different numbers of *smr* robots. (a) Experiment with three robots. (b) Experiment with 18 robots.**

Mobile robots equipped with gas sensors delimit the gas expansion area, making it possible to verify the behavior of the gas in the environment in question. As a result of this detection, a real-time dynamic map was generated corresponding to the variations in the gas levels detected in the environment. Figure 14 shows the result of this mapping over time in a multi-robot system with 18 robots.

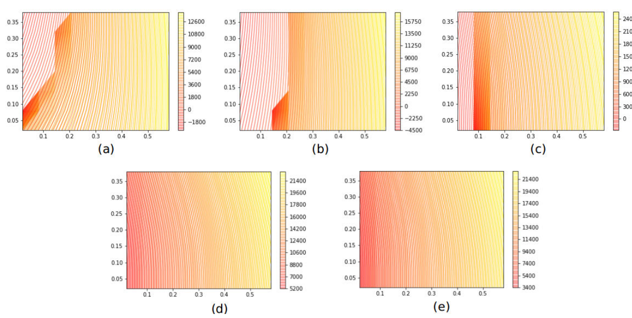

FIGURE 14. **Variation over time in gas mapping considering eighteen robots at different time points. (a) t(10%). (b) t(20%). (c) t(50%). (d) t(70%). (e) t(100%).**

The scalability of the multi-robot system was varied, considering 3, 6, 12, 18, 24, and 30 robots. Furthermore, each experimental configuration was repeated 10 times, with 60 experiments, to verify the different patterns in the results and guarantee their reliability. Figure 15 presents the results of the different scalability levels for a time instant of 10% for the total time.

During the experiments, information was collected on the gas concentration, the distance traveled by each robot, and the final position of each robot until the gas concentration level was detected, as shown in the flow chart in Figure 16.

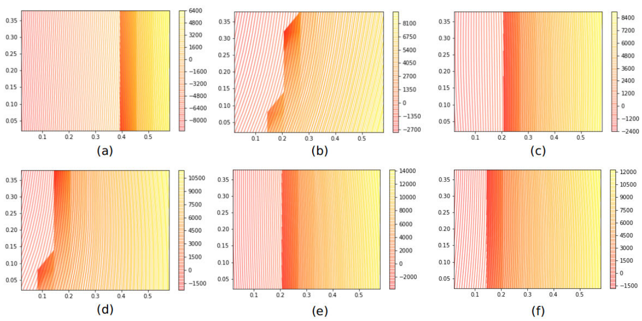

FIGURE 15. Variation over time in gas mapping considering eighteen robots at different time points. (a) SMR - 3 robots. (b) SMR - 6 robots. (c) SMR - 12 robots. (d) SMR - 18 robots. (e) SMR - 24 robots. (f) SMR - 30 robots.

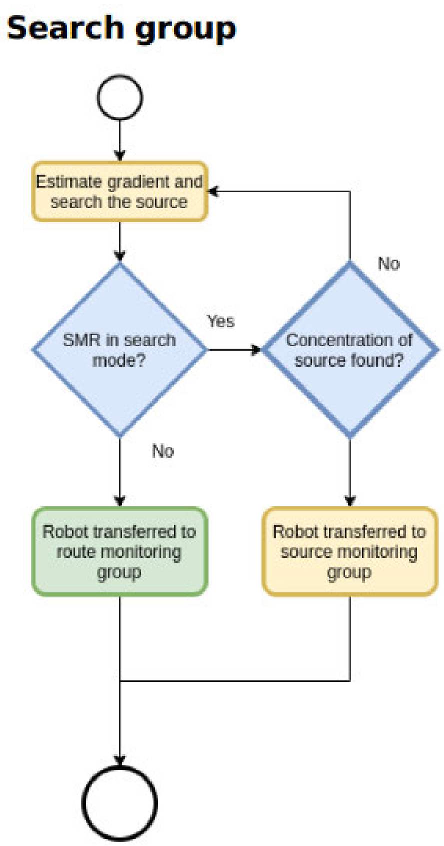

FIGURE 16. Gas source search flowchart.

TABLE 2. Main results of the second experiment.

NR	Var. Sum. Ideal X Real	Global/robot (m)	Abs. error (m)	Rel. error	Var. Conc. MAX e MIN
3	1,24%	0,0047	0,086	-	16,00%
6	5,86%	0,0141	0,090	4,02%	48,06%
12	2,63%	0,0068	0,118	36,78%	53,95%
18	6,55%	0,0197	0,139	60,90%	66,05%
24	7,95%	0,0220	0,143	65,35%	52,86%
30	9,73%	0,0258	0,139	60,90%	92,72%

The main objective of this experiment was to verify the gas mapping capability through a multi-robot system until high levels of gas concentration close to the gas source were found. Table 2 summarizes the primary data collected throughout all the experiments.

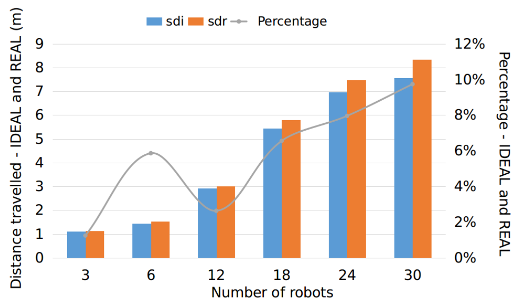

FIGURE 17. Comparison between the average of the sum of distances traveled by robots. sdi - summation of the ideal distance, sdr - summation of the real distance.

After analyzing all the data for the approach proposed in this section, it was possible to verify a significant percentage increase when comparing the sums of ideal and real distances. Therefore, the increase in the number of robots resulted in a percentage variation between 1.24% and 55.99% in the sum of the average distances covered. Figure 17 shows this information.

In addition, it is possible to verify that the SMR composed of 3, 6, or 12 robots has high efficiency compared to systems that have 18, 24, or 30 robots because the less scalable systems run trajectories with lower energy expenditure. As the number of robots increased, a worsening in the efficiency of the trajectory was observed, as shown in Figure 18.

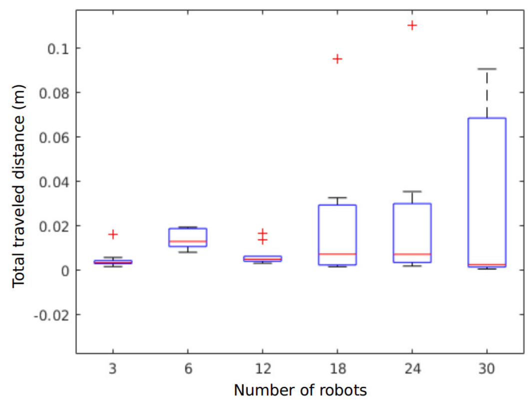

FIGURE 18. Individual analysis of the distances covered by each robot according to different SMR scalability levels in experiment 2.

Another significant result is the average of the final robot distance from the gas source. This is because the system's increase in scalability also resulted in distances farther away from the source, as shown in Figure 19.

Other data were also calculated and collected to verify the robot's performance regarding movement and precision in the experiments. The ratio between real and ideal displacement was to verify which robots perform better movements and avoid unnecessary displacements until they complete their tasks. The smaller the value, the fewer the deviations until

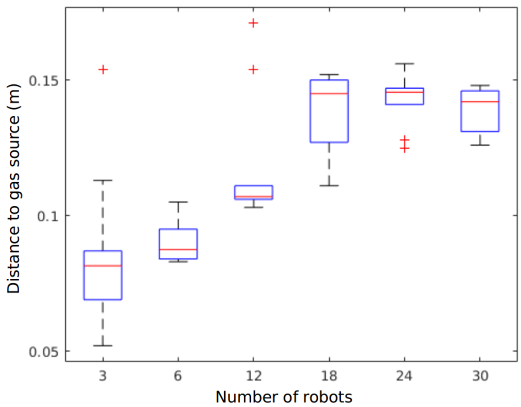

FIGURE 19. Average distances from robots to gas source according to different SMR scalability levels.

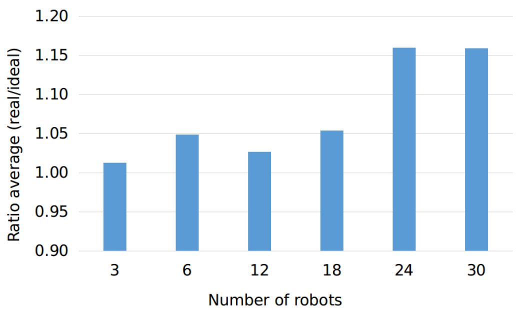

FIGURE 20. Average of the ratio between real and ideal distances covered.

the end of the experiment. Figure 20 summarizes this information.

The final distance of the robot from the exact position of the gas source was verified. The results demonstrate that the mean of the standard deviations of the final positions of the robots maintains a level of variation close to 0.055, even with an increase in the number of robots. The final position of the SMR containing 3 robots was positioned closer to the exact location of the gas source. Another piece of information that corroborates the information mentioned above is the tendency to stabilize the final distances of the robots relative to the source. This information is shown in Figure 21.

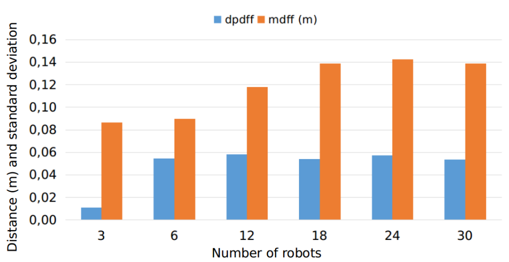

FIGURE 21. Mean of the standard deviations of the robots' final positions, and mean of the distances from the gas source, considering the variation in the scalability of the SMRs. ***mdff (average of the final distance to source (m)), dpdff (standard deviation of final distance to source).***

However, when the scalability of the SMR was increased, systems with a larger number of robots showed greater individual precision. At least one of the robots was placed close to the gas source. On the other hand, when there are few robots in the SMR, they keep close distances from each other to the gas source. These results are shown in Figure 22.

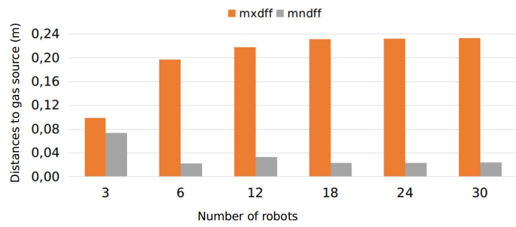

FIGURE 22. Comparison between the averages of the maximum and minimum distances according to different topologies of the SMRs. ***mxdff (average final maximum distance to source), mndff (average final minimum distance to source).***

The SMRs collected data that presented information on the gas concentration levels during the experiments. Thus, it was possible to assess the final concentration of the gas to verify the impact of different levels of scalability of the system on the results. In Figure 23, it was possible to verify that *mcf*, *mxcf*, and *mncf* of the robots have a stability level similar to 2000 in the RS/R0 ratio (which corresponds to a high gas concentration) considering systems with up to 24 robots.

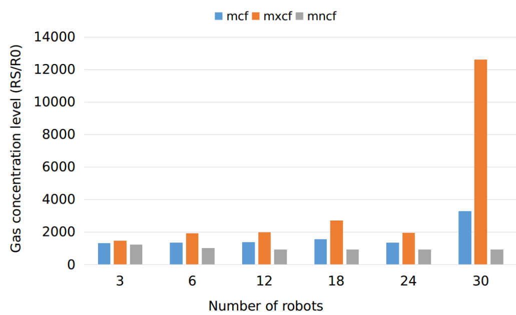

FIGURE 23. Average, maximum, and minimum gas concentration. ***mcf - average gas concentration, mxcf - average maximum gas concentration, mncf - average minimum gas concentration.***

When the total number of robots is 30, the data are influenced by outliers due to the number of robots present in the experiment. The high number of robots in the experiment, associated with the repulsion that the potential fields exert on each other, means that not all robots can reach regions with a greater gas concentration. Another fundamental analysis is between the measured concentration values and the final average position of the robots. As the scalability of the SMR increases, the average distance from the source also increases, as shown in Figure 21. However, when the number of SMR robots exceeded 18, the average final robot position was substantially stable at a high threshold. The results presented bioinspired behavior only in the quorum sensor, and chemotaxis of the bacterial colonies indicated lower and upper limits to the scalability of multi-robot systems. The appropriate amount varied according to the expectation of the expected results.

However, the best results were obtained at levels 3, 6, and 12 of the robot SMR. From 18 robots onward, the results showed stability at inefficient levels. Therefore, in the next sections, new cognitive mechanisms, bioinspired by bacteria, will be introduced to the behavior of multi-robot systems within maximum scalability with 18 robots. These findings are shown in Figure 24.

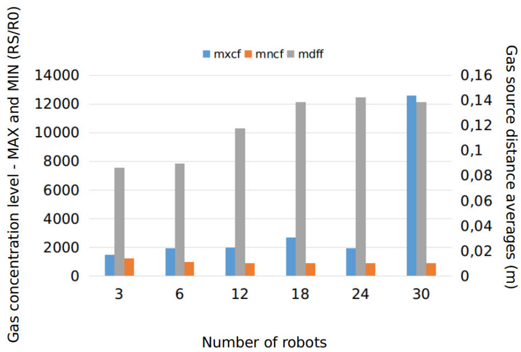

FIGURE 24. Analysis of measured extreme concentrations and average final position of robots.

D. COLLECTIVE DECISION-MAKING

This section is to explores the different levels of complexity for gas mapping. Thus, a third cognitive mechanism for robot behavior was added. The concept of *sporulation* was explored by varying the number of robots used to map the environment. Biological colonies of bacteria can increase or decrease the number of individuals, depending on the collective interest. The collective decision-making experiment helps to vary the number of robots and the distribution of the task to be performed. A variation in the scalability of the multi-robot system, trajectory information, and gas concentration was used to determine the timing of another task assignment. Thus, some robots have their tasks changed to create safe routes in the environment instead of just mapping.

The scalability of the multi-robot system has, as a parameter, the results presented in the previous section and the necessary characteristics for creating a safe route. Therefore, new experiments were carried out considering 3, 6, 12, and 18 robots. After the robots find the region of high gas concentration (next to the gas source), a group of robots is destined to create a safe route in the monitored environment. Thus, spores that delimit a safe route in the environment are created. Table 3 summarizes the main parameters used in this approach.

Initially, all the robots in the experiments were designed to identify the regions with the highest gas concentration. Thus, every robot heads to regions close to the gas source. Subsequently, each experiment had a different number of robots to continue mapping and creating safety routes. The premise adopted in this experiment is to verify and guarantee

TABLE 3. Initial parameters of the experiment. NR (number of robots).

Experiment	First	Second	Third	Fourth
NR - total	3	6	12	18
NR - mapping	1	4	8	12
NR - route	2	2	4	6

maximum efficiency with the minimum energy cost of the system. Thus, the minimum number of robots was intended to build the safety route.

The minimum amount to check a possible route is 2 robots based on the gradient calculation approach presented in Section 5.2.3. With the increased scalability of the multi-robot system, it was possible to verify the differences between using a larger number of robots to build safe routes. These routes are based on the cognitive mechanisms of *sporulation* and negative *chemotaxis*.

They look for low concentrations of gases, resulting in movements in the opposite direction to chemical stimuli. Furthermore, the images shown in Figure 25 make it possible to verify the *spores* that delimit the safe region built by the multi-robot system.

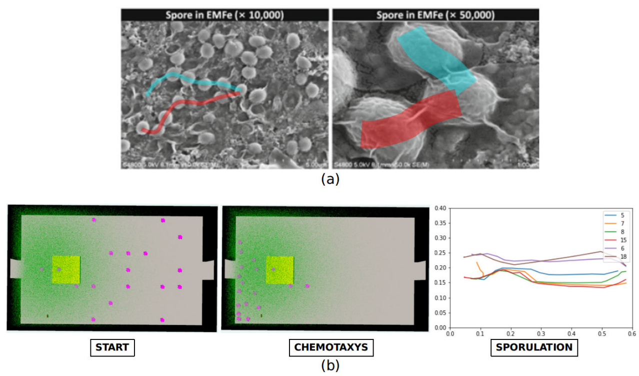

FIGURE 25. (a) Sporulation of a real bacterial colony [26]. (b) Creation of a safe bioinspired pathway in bacterial sporulation.

Thus, it is clear that the increase in the system's complexity that involves bioinspiration in the cognitive mechanism of *sporulation* has raised it to a new level of complexity, considering the assignment of a new task with the creation of a safe route. The *sporulation* explored throughout these experiments dealt with creating safe routes. This process assumes that the gas source region and its high concentrations have already been found. Thus, a group of robots is assigned to create this route by adopting *negative chemotaxis*. The points of interest of these robots are the entry and exit of the environment in which the robots are considering a path with a low level of gas concentration. Thus, while a group of robots is responsible for maintaining the updated map of the region with a high gas concentration, another group is directed to create the route, as shown in Figure 26.

The results on the safe routes generated using this approach are summarized in Table 4.

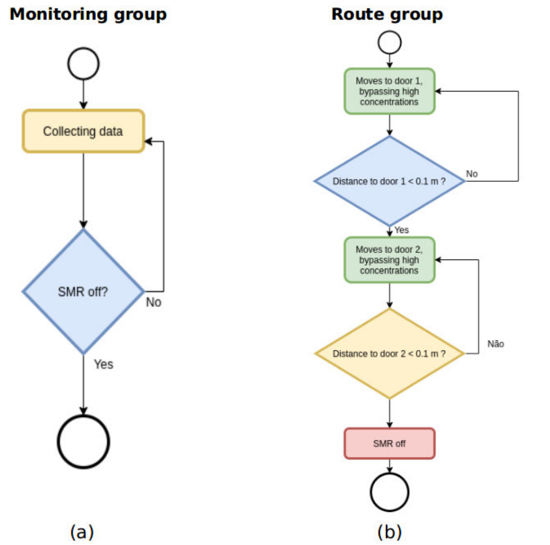

FIGURE 26. Flowcharts: (a) environmental monitoring and (b) route creation.

TABLE 4. Results regarding the safe routes of the third experiment.

NR	AVG displac. (m)	AVG Conc.(RS/R0)	AVG Conc. MAX(RS/R0)	AVG Conc. MIN(RS/R0)
3	2,867	8311	18321	2841
6	0,624	9363	16843	2310
12	0,615	5984	13233	1567
18	0,560	2747	9081	1247

Other results also demonstrated the system's difficulty finding an adequate safe route given the characteristics involved in this experiment, where three cognitive mechanisms are implemented (*quorum sensor, chemotaxis, and sporulation*), as can be seen in Figure 27.

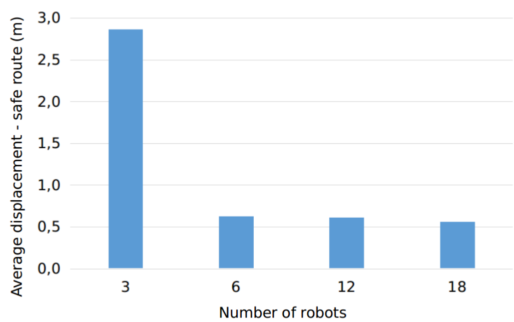

FIGURE 27. Analysis of the distances covered by the robot according to different levels of scalability of the SMR in experiment 3.

The results of these experiments are summarized in Table 5, where *Abs.*, *Rel.*, and *Conc.* mean *Absolute*, *Relative*, *Concentration*, respectively.

E. COLLECTIVE MEMORY TRANSFER

The last level of complexity of the system was the integration of the four cognitive mechanisms addressed in this work: the *quorum sensor*, *chemotaxis*, *sporulation* and *conjugation*.

TABLE 5. Main results of the third experiment.

nr	Var. Sum. ideal X real (%)	Global analysis/robot (m)	Abs. error (m)	Rel. error - 3 robots (%)	Var. Conc. MAX e MIN (%)
3	5,78%	0,0084	0,155	-	0,00%
6	18,65%	0,0279	0,141	-8,56%	39,15%
12	19,26%	0,0202	0,139	-10,09%	60,93%
18	51,74%	0,0620	0,144	-6,93%	60,46%

Thus, the system was complete for experimentation. Similar to the experiments presented in Section 5.3.3, the multi-robot system must search for the gas source and subsequently search for new safe routes. The difference in this experiment is the maintenance of collective memory from the beginning of tasks. Figure 28 presents a flow chart summarizing the collective decision-making of the multi-robot system.

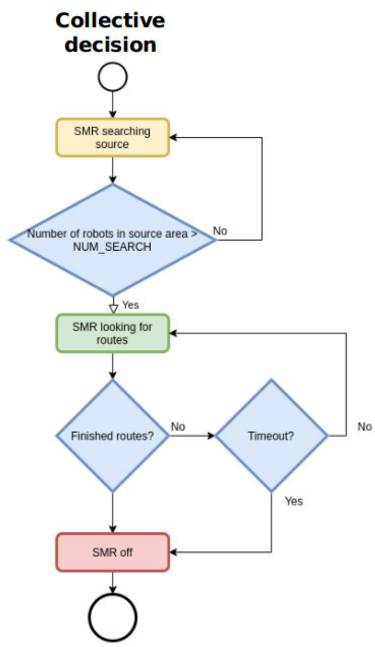

FIGURE 28. Flowchart referring to collective decision making, bioinspired by the cognitive mechanism of ***sporulation***.

The initial parameters of this experiment were the same as those presented in Table 3. Again, 40 experiments were performed, collecting information on the cost involved in using the trajectories to search for the gas source, create a safe route, measure the gas concentration, and the distance from the gas source. The results involving the SMR with 6 and 12 robots were better at most points. The values were the smallest in the second column, where the values between the ideal traveled distance (Euclidean distance) and the real distance (performed path) were compared.

In addition, the third column, which indicates the average distance traveled by the robots in each SMR value, also proved to be more efficient. Another critical factor is seen in the last column, where the values represent the extreme gas concentrations measured by the robots. This information allows us to distinguish those who arrived at higher and lower levels of gas concentration.

TABLE 6. Results regarding the safe routes of the fourth experiment.

nr	Average displac. (m)	AVG Conc. (RS/R0)	AVG Conc. MAX (RS/R0)	AVG Conc. MIN (RS/R0)
3	0,817	8591	16361	2856
6	0,637	5650	12218	1441
12	0,611	5390	13419	1137
18	0,553	5818	19624	1287

TABLE 7. Main results of the fourth experiment.

nr	Var. Sum. ideal X real (%)	Global analysis / robot (m)	Absolute error (m)	Relative error - 3 robots (%)	Concentration MAX e MIN (%)
3	22,42%	0,0609	0,105	-	41,34%
6	9,93%	0,0320	0,152	45,19%	86,26%
12	19,54%	0,0417	0,147	40,38%	92,86%
18	34,05%	0,0829	0,134	28,24%	92,92%

Table 6 summarizes the primary data collected regarding the safe routes created in this experiment.

The experiments containing 18 robots showed a shorter trajectory compared to the other SMRs, but the mean gas concentration was higher than the levels observed with 6 and 12 robots. On the other hand, the extreme concentrations show results that demonstrate the multi-robot systems with 18 robots detect the regions with the lowest gas concentration, and the systems with twelve robots detect the highest gas concentrations. For all parameters, the experiments consisting of 3 robots showed less efficient results than the others. This approach's improvement is evident compared to the approach in Section IV-C, as the reduction of distances traveled by robots, mainly in the SMR of 3 robots, is approximately 72%. The distances were similar for the other scalability levels. Table 7 summarizes the main data collected from these experiments.

Figure 29 shows the variation in the trajectories performed according to the different scalability values of the multi-robot system.

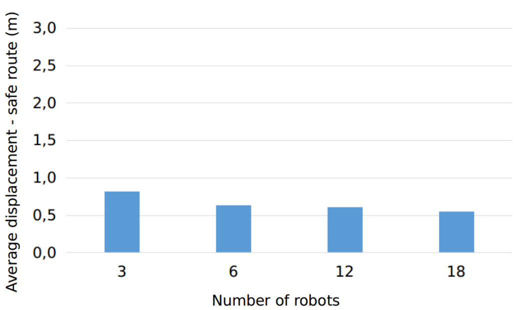

FIGURE 29. Analysis of the distances covered by the robot according to different levels of scalability of the SMR in experiment 4.

V. COMMON ANALYSIS OF RESULTS

After gathering all the data for the approaches proposed in this work, analyses were performed to verify possible improvements and differences of each approach. The first data involved referring to the average distance covered by the robots. It is important to note that in the second experiment, the robots only mapped the environment. In the third and fourth experiments, robots were also required to create safe routes. Figure 30 presents the data for this situation.

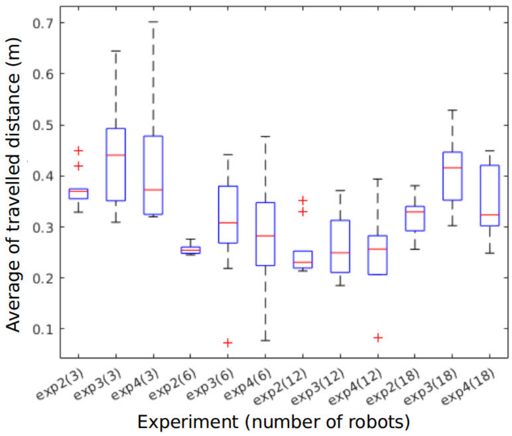

FIGURE 30. Comparative analysis of the means of distances covered by robots considering different levels of cognitive approaches of the multi-robot system.

The terms presented in this work as **exp2**, **exp3**, and **exp4** refer to approaches 2, 3, and 4, respectively, as shown in Figure 3. In this analysis, it is possible to observe that, as expected, the robots in the second experiment developed a lower average of the distance covered, given that they had only one task. However, the more complex cognitive approach of the fourth experiment represents an improvement in efficiency compared to the third experiment, where the implemented algorithm has only instantaneous information for mapping and route generation. Furthermore, the results with 6 and 12 robots showed better efficiency in the average displacement of the robots.

Another observation refers to the absolute values and the sum of the distances covered by all robots at different SMR scalability levels. Through these data, it is possible to verify that even with more than one task to be performed in the third and fourth experiments, depending on the scalability level, the developed approach was able to present results very close to or even better than the second experiment that required only the mapping task. These situations are illustrated in Figure 31.

Other information extracted from these experiments, which corroborates the previous results, is reflected in the average distance traveled by the robot at different levels of scalability of the SMR, as can be seen in Figure 32, where the average distance has more efficient values in the SMRs with 6 and 12 robots.

The number of maneuvers involved in the different approaches show that the memory inserted into the robots improves this situation in most experiments, as the distance traveled by the robots is smaller than the *sporulation* approach. This is evidenced by the ratio between the ideal distance (Euclidean distance between the initial position and the source) and the actual distance covered by the robots having a performance improvement when compared

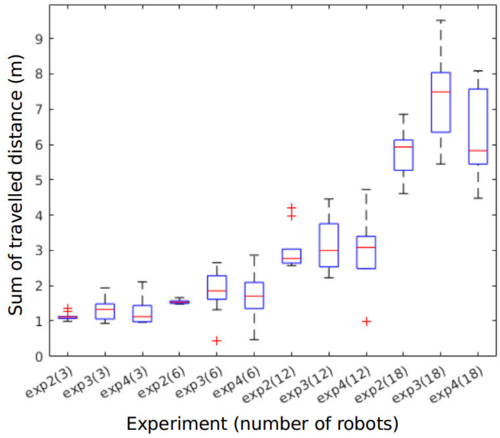

FIGURE 31. **Comparative analysis of the sums of distances traveled by robots considering different levels of cognitive approaches of the multi-robot system.**

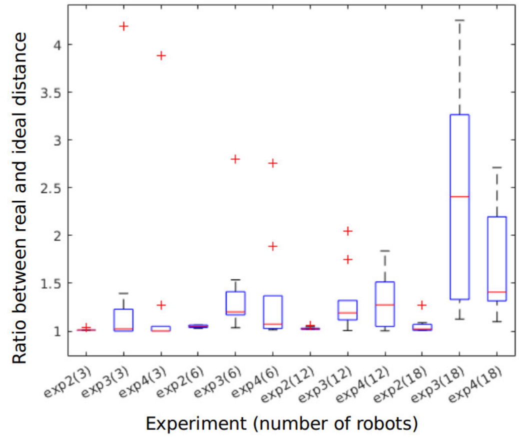

FIGURE 33. **Comparative analysis of distances traveled by robots considering different levels of cognitive approaches of the multi-robot system.**

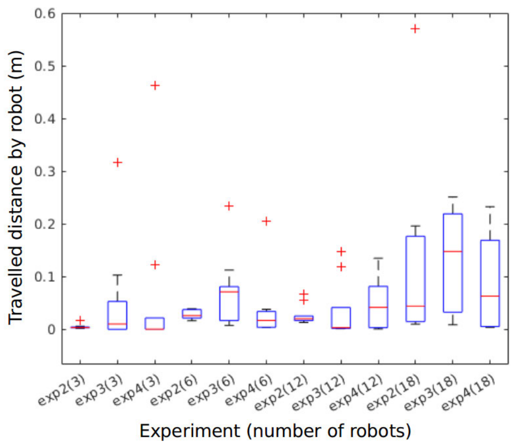

FIGURE 32. **Comparative analysis of distances traveled by robots considering different levels of cognitive approaches of the multi-robot system.**

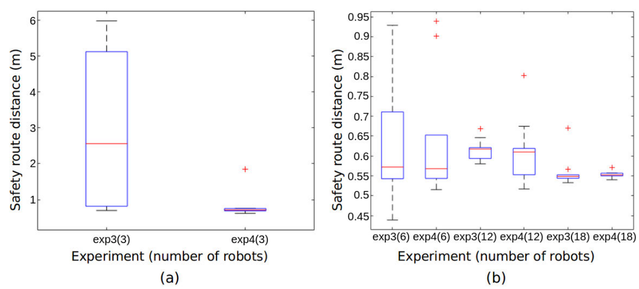

FIGURE 34. **Effective distance of escape routes considering different levels of cognitive approaches of the multi-robot system.**

to the approaches in Section IV-C (no memory - exp3) and Section IV-D (with memory - exp4). These are shown in Figure 33.

Thus, primary data from the experiments were compiled. Table 8 compares the results of the third and fourth experiments with those obtained in the second experiment.

Thus, it is possible to state that comparing the three different approaches, considering all the levels of scalability presented, the average energy expenditure of the third experiment was 17.1% higher than those presented in the second experiment. The fourth and most complex cognitive system presented showed an increase of 7% compared to the second approach.

The latest data collected compares the performance of safe routes created by multi-robot systems. Figure 34 shows the performance with respect to the effective distance of the routes. Due to the large discrepancy of the experiments considering the approach with three robots.

Other essential data refer to the average gas concentration levels detected throughout the experiments. Because this information represents the accuracy and exploratory capacity of each SMR, this information can be verified from Figure 35.

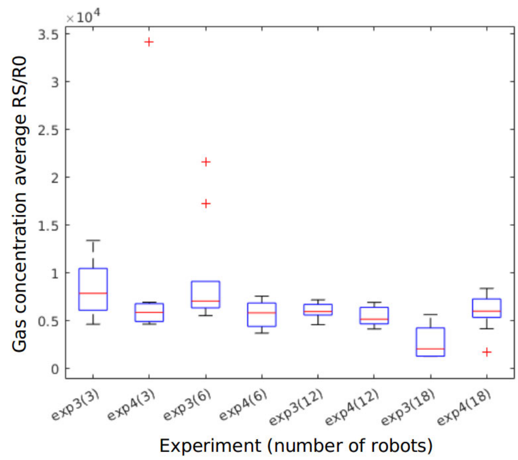

FIGURE 35. **Average gas concentration levels of the routes.**

The extreme gas concentration levels represent the maximum and minimum gas concentration values (RS and R0) detected throughout the experiments. The MAX value, shown

TABLE 8. Comparative summary of different cognitive approaches.

NR	3		6		12		18	
exp. N	exp3	exp4	exp3	exp4	exp3	exp4	exp3	exp4
displac. AVG	17,9%	12,5%	20,4%	8,5%	5,4%	-0,2%	24,9%	7,3%
robot displac.	902,8%	1181,8%	297,6%	104,9%	417,1%	511,0%	591,0%	321,9%
ratio (real x ideal)	37,7%	30,5%	33,3%	29,8%	27,6%	29,0%	126,5%	61,3%

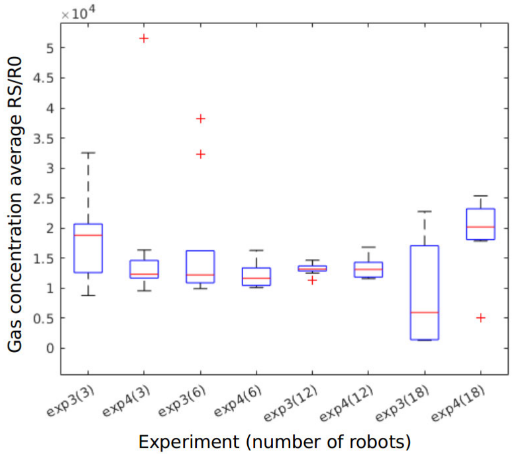

FIGURE 36. Extreme gas concentration levels of routes.

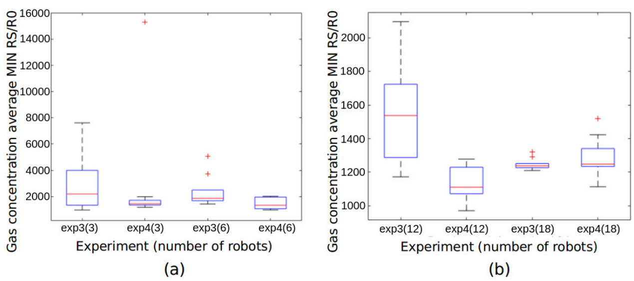

FIGURE 37. Average gas concentration levels of the routes.

in Figure 36, represents the lowest concentration of harmful gases.

Both approaches showed similar results, with values between 1 and 1.5 in the average concentration of MAX gas. Only experiments with 3 and 18 robots showed a more significant difference, with values between 0.2 and 2.5.

However, the values shown in Figure 37 refer to the values with the highest gas concentration MIN, representing the detections with the highest level of danger. The higher the RS/R0 value, the lower the gas concentration. When the value of RS/R0 was smaller, the concentration level was higher.

The data summarized in Table 9 represent an improvement in creating safe routes using the more complex cognitive approach of the fourth experiment.

Figure 38 presents the average of the safe route values performed by the multi-robot systems considering the bioinspired cognitive approaches presented in the third and fourth experiments.

TABLE 9. Comparative route summary.

Experiment	exp 3	exp 4	Var. %
Route (m)	1,17	0,50	57,48
AVG conc.	6601	6362	3,62
AVG conc. MAX	14369	15405	7,21
AVG conc. MIN	1991	1680	15,62

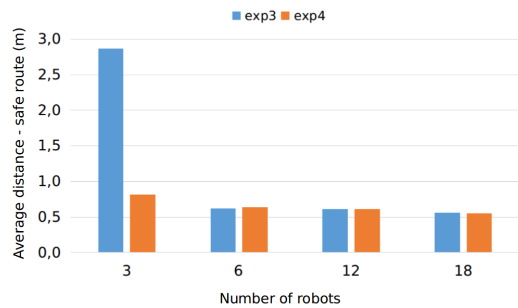

FIGURE 38. Average displacement of safe routes presented in the bioinspired approaches of the third and fourth experiments. *exp3 (Approach 3), exp4 (Approach 4).*

In *exp3 - 3* robots, there was no memory of the information collected throughout the experiment. The amount of data collected in the environment by 3 robots was not sufficient for the displacement to be efficient.

Thus, it is noticeable that the amount of information collected in the environment during the experiments directly influences the safe routes created by the multi-robot systems. As data sampling increases, the difference between efficiency is practically zero, as observed in experiments with 6 robots. Another situation that corroborates this conclusion is that in the fourth experiment with 3 robots, the route created by the SMR was much more efficient than in the third experiment with 3 robots, as the amount of information regarding the environment in these two experiments was different.

Furthermore, it is possible to verify that the gradient resulting from the direction of the robots throughout the experiments follows the exact gas concentration trend in the environment, thus generating a dynamic potential field. This can be seen in Figure 39.

VI. DISCUSSION

This work presented a new approach for bioinspired and collective multi-robot system applications. This approach can be applied for various purposes, such as collective monitoring or gas mapping in different environments. Mobile robots search for gas and move autonomously, bioinspired by the

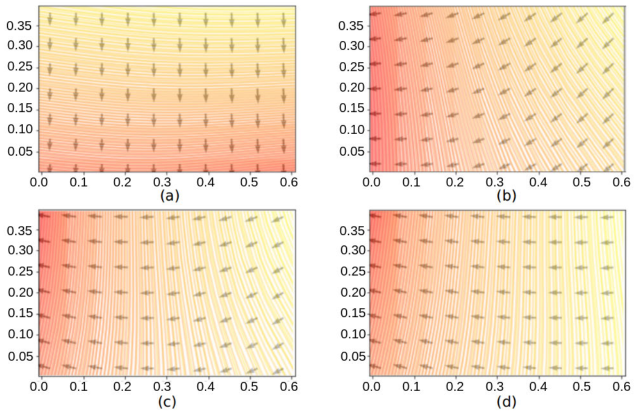

FIGURE 39. Resulting potential field at different instants of time considering the experiment with 3 robots. (a) t(20%). (b) t(50%). (c) t(70%). (d) t(100%). Image units are in meters (m).

cognitive behavior of bacteria, where efficient mapping is their primary objective. In the case of mobile robots, they must find their 'food' (high gas concentrations), avoid contact with "antibiotics" (structure boundaries or unwanted areas), and, during collective behavior, avoid other mobile robots. Directed locomotion through gas concentration gradients is a suitable approach for environments subject to airborne contamination.

The experiments were conducted in an environment where the wind speed was low. Thus, it was possible to observe variations in the gas concentration at different points in the environment. After stabilizing the gas concentrations, the mobile robots searched for the gas source and mapped the environment. The results presented in this study demonstrate that good robots can explore the environment according to their size. Furthermore, it was noted that different gases did not influence the system with multiple robots implemented throughout the experiments after the gas dispersion stabilized.

Another aspect of the analysis is the improvement achieved in the collective work between mobile robots, with efficiency in exploration being the most significant issue. Another necessary check is the ideal number of robots in each type of experiment: ideal scalability in different contexts and situations. Depending on the size of each robot and the environment in question, some limits can result in better efficiency in the tasks of multi-robot systems.

According to the results obtained from the experiments involving high levels of cognitive complexity, the main factor influencing the improvement of the results is the number of samples collected in the environment. These data can be obtained from a sizeable multi-robot system or a minor system with a large memory capable of storing and processing values for an extended period, adding greater assertiveness in collective decision-making. The amount of data available in each experiment mainly influenced the absolute values of the safe routes performed by the multi-robot systems. Therefore, when the number of robots is small, the cognitive approach that uses conjugation significantly influences the result. As the number of robots increased during scalability variations, the difference between displacements remained constant in their values. However, the more complex cognitive system presents better precision in developing its route, as it detects more extreme values in gas concentration. It manages to map more harmful regions for possible evacuation and maintenance in environments containing gases.

A. OPEN RESEARCH QUESTIONS AND FUTURE DIRECTIONS

While this study provides a solid foundation for applying bioinspired multi-robot systems, several important research questions remain open for future investigation. One of the primary areas for future research is how these systems can be applied in environments with varying and unpredictable conditions, such as fluctuating wind speeds or sudden changes in gas concentration levels. Exploring how the robots' cognitive behaviors can adapt to such dynamic conditions will be critical for ensuring their robustness and effectiveness in real-world applications. Additionally, the potential integration of more advanced artificial intelligence techniques, such as machine learning, could further enhance the robots' decision-making capabilities and adaptability in complex environments.

Moreover, while the gas leakage problem is a critical use case in this study, the proposed multi-robot operation approach has broader applicability and can be generalized to other domains. For instance, similar bioinspired systems could be employed for environmental monitoring, such as detecting contaminants in water sources, mapping air pollution in urban areas, or even in search and rescue operations, where robots might need to locate survivors in hazardous or disaster-stricken environments. In addition, in healthcare, micro and nanorobots inspired by similar principles could revolutionize medical treatments, offering new possibilities for minimally invasive surgeries, targeted drug delivery, and precise diagnostic procedures. These robots could autonomously navigate the human body, identifying and treating diseases at a cellular level, offering significant advancements in cancer treatment, vascular surgeries, and other medical fields. Future work should explore how this approach can be adapted to diverse domains, ensuring the system's scalability and versatility across various industries and applications.

Another area that warrants attention is optimizing robot path planning to avoid overlap and redundancy. While this study focused on collective exploration, future work could investigate more sophisticated algorithms that ensure each robot covers new areas efficiently without retracing previously explored paths. It would not only improve the energy efficiency of the robots but also allow for faster mapping of hazardous environments.

B. PRACTICAL APPLICATIONS AND MANAGERIAL SIGNIFICANCE

Industries dealing with high-risk environments, such as gas leak detection and environmental monitoring, can significantly benefit from the results of this study. One possible scenario for practical application could be in large industrial plants where gas leaks are a critical safety concern. As developed in this study, multi-robot systems could autonomously explore and monitor such environments, identifying potential leaks and hazardous areas in real time, thus reducing the need for human workers to enter dangerous areas.

Additionally, future research could explore the use of these systems in emergency response situations, where the rapid identification of hazardous zones could be critical for evacuating personnel and mitigating risks. Beyond gas leaks, these systems could be applied in various industrial settings for tasks like radiation detection, chemical spill monitoring, and even detecting structural weaknesses in buildings. In healthcare, micro and nanorobots could be designed to perform tasks such as clearing blocked arteries, delivering drugs to specific sites, or even conducting surgeries with minimal invasion, improving recovery times and reducing patient risks. An illustrative scenario-based evaluation, where robots are deployed in a simulated industrial facility to detect and map hazards or in a medical scenario to perform minimally invasive procedures, could demonstrate these systems' real-world utility and impact. It would allow a clearer understanding of how the proposed approach could be practically applied and managed in different industries, including healthcare. By addressing these open research questions and exploring practical applications across multiple domains, including the healthcare industry, future studies can build on the foundation laid by this work. This approach would further refine and expand the potential of bioinspired multi-robot systems, ensuring their relevance and adaptability in diverse real-world contexts, from industrial applications to groundbreaking healthcare innovations.

C. CHALLENGES IN REAL-WORLD APPLICATIONS VS. SIMULATION ENVIRONMENTS

While this study successfully demonstrated the viability of bioinspired multi-robot systems in a simulation environment, specific challenges may arise when transitioning to real-world applications. Simulations offer controlled conditions where variables such as wind speed, gas concentration, and robot interactions can be precisely managed. However, real-world environments introduce unpredictability that may affect the accuracy of robot positioning, pathfinding, and mapping. Factors like uneven terrain, unexpected obstacles, sensor inaccuracies, and fluctuating environmental conditions (e.g., sudden changes in wind direction or temperature) could lead to the robots' behavior deviations.

In real-world settings, noise might affect sensor data, leading to less accurate localization and mapping of gas concentrations. Robots may need help maintaining precise positioning, especially in complex or dynamic environments, potentially reducing the efficiency of collective behavior. Additionally, physical obstacles could hinder robots' movements, causing delays or inefficiencies in exploration tasks that were not encountered in simulation. Another aspect to consider is the energy consumption of robots in real-world conditions. While simulations often assume ideal energy usage, real robots must account for battery life, especially during extended operations in harsh or remote environments. It introduces the need for more sophisticated energy management and recharge strategies, which were unnecessary in a simulated context.

In summary, while the simulation environment provided valuable insights into the potential of multi-robot systems, future research must address these real-world limitations by refining sensors, navigation algorithms, and energy optimization strategies to ensure reliable and scalable performance in practical applications.

VII. CONCLUSION

The results presented in this work demonstrate that the simulated experimental system provides a valuable platform for researchers to test various algorithms, configurations, and arrangements of multi-robot systems, particularly in hazardous environments where human intervention is limited or dangerous. Simulating hazardous environments, such as those subject to gas leaks, allows for more accurate predictions of real-world applications, ensuring that the developed systems can respond effectively in critical situations.

Furthermore, the study highlights the importance of determining the optimal number of robots for different operational contexts. The data suggest that the number of robots directly impacts the efficiency of exploration and detection tasks, with larger systems offering greater accuracy in mapping hazardous areas. This knowledge can guide future research, helping to refine multi-robot configurations for specific scenarios, including indoor environments prone to gas leaks or contamination.

An important finding related to this is the potential effect of the scanned area and the number of robots on system performance, as highlighted in the feedback received. According to the results and graphs presented in this study, the saturation point for the system's performance varies depending on the cognitive behavior implemented. Thus, a relationship exists between the number of robots deployed and the efficiency achieved, suggesting that beyond a certain point, adding more robots may yield diminishing returns in terms of mapping accuracy and exploration efficiency. This analysis could lead to a deeper understanding of how cognitive approaches influence the scalability and effectiveness of multi-robot systems.

Another critical factor to consider in future research is optimizing path planning to prevent overlapping areas already covered by the robots. By ensuring that each robot follows an optimized, non-redundant path, the system's overall efficiency can be significantly improved, reducing unnecessary energy expenditure and ensuring faster, more comprehensive coverage of the target area.

Furthermore, the scalability of these robotic systems, down to micro and nano scales, was feasible based on the cognitive approaches and strategies explored in this work. It opens up significant possibilities for future applications in environments where precision and minimal invasiveness are required, such as industrial maintenance, environmental monitoring, and even medical applications where micro-scale robots can perform targeted operations.

Future work could explore integrating more advanced artificial intelligence and machine learning techniques to enhance the decision-making capabilities of these robots. Investigating dynamic environments with variable wind speeds, unpredictable gas leaks, and more complex obstacles would provide further insights into the robustness of these systems in real-world conditions. Furthermore, future studies could focus on energy efficiency and battery life, especially for large-scale systems where power management is critical in ensuring continuous operation. Additionally, developing more precise sensing technologies and lightweight materials could enhance the performance of micro- and nano-robots, enabling them to address a broader range of applications.

In conclusion, the research contributes valuable insights into the development and scalability of bioinspired multi-robot systems, providing a framework for future studies to build upon. The ability to handle complex environments, detect concentrations of harmful gases, and optimize robot deployment demonstrates the system's potential to improve safety and efficiency in high-risk environments. These findings, particularly the critical aspect of optimizing paths to prevent overlapping coverage, will set a standard for future developments in collective robotics and its use in complex environments. They will serve as a benchmark for future advances in collective robotics and its applications in challenging environments.

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