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Collective Gas Sensing in a Cyber-Physical System

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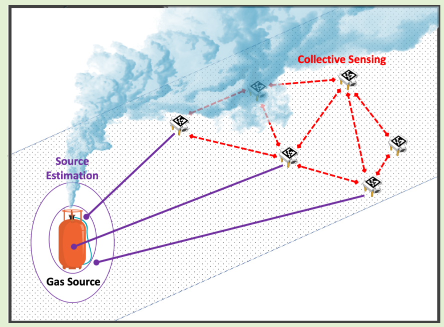
***Abstract*—This paper discusses a novel collective sensing approach using autonomous sensors specially designed to monitor gas leaks and search for gas sources. The proposed collective behavior aims to improve the gas-source search by sharing information between mobile sensors and reducing the risks associated with gas leakage. The group acts as a composite sensor that can move independently to search for an optimal sensing zone. The autonomous searching behavior is bio-inspired by colonies of bacteria that continuously seek energy sources throughout their existence. Each sensor makes its own autonomous search decision, considering the group sense, to move in the direction of a better energy source. The collective approach is based on autonomous agents sharing information to achieve a collective sense of gas perception and utilizes more intelligent searching. The method is evaluated in a cyber-physical system specially developed to safely experiment with gases and mobile sensors while reproducing the realistic dynamic behavior of the gas. Experiments are performed to clarify the collective gas-sensing contributions, and the gas search is compared through multiple mobile sensors with and without collective sensing. The proposed approach is evaluated in an unhealthy environment to elucidate its effectiveness. In addition to presenting the related differences between collective and individual sensory approaches, this work contributes with analyzes of the scalability of mobile gas sensing systems. This work also contributed as a simulated semi-physical experimental system to test algorithms' performance before applying it to practice.**



***Index Terms*—Collective sensing, mobile sensor, and bio-inspired.**

I. Introduction

THE industrial sector usually uses gas as a fuel for process heating, combined heat with power systems, and other applications. The gas employed is highly flammable and poses a high risk to people's safety and the physical integrity of industrial plants. Gas-leak monitoring is mandatory in the industry to avoid accidents.

The traditional approach employs multiple *fixed* sensors distributed around an industrial plant to cover a large area. This sensing type restricts measurements at previously defined coordinates, limiting the sensing range. Another significant factor is the many sensors needed to predict the location of the gas source for acceptable reliability. The gas behavior is unpredictable and strongly dependent on several external factors with innumerable characteristics that cannot be monitored reliably using fixed sensors without comprehensive sampling. The use of fixed sensors leads to delays and errors in identifying the leak and location of the source, thereby increasing the risk of accidents. Gas monitoring has several actual challenges, according to [1]–[3], such as

- proper location of sensors,
- localization of gas source in an unknown environment,
- time and cost to find the gas source,
- spatial estimation of gas dispersion, and
- experimentation of novel approaches.

Industrial facilities generally have large areas with several gas transmission lines. Leakage monitoring is highly dependent on sampling, i.e., the number of sensors employed. However, as the gas dispersion is not linear, the sensor distribution should not be, either. Even installations that correctly follow fixed sensor installation standards are subject to "blind" areas, where the gas leak cannot be detected due to the

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gases' dynamics. The gas source estimation will also be inaccurate without an adequate distribution of sensors, sensing their dispersion. However, each leak has a different optimal distribution, making accurate monitoring with fixed sensors unlikely. Inaccuracies can result in delayed leak detection and source identification, which increases the associated costs and risk of accidents.

Gas-leak sensing requires dynamic reconfiguration of gas sensors, which can only be achieved through mobile sensors. The concept of collective sensing can be applied to introduce a new class of intelligent gas sensors that move autonomously in the environment to search for leaks. This approach allows sensors to always remain optimal for gas sensing, thereby improving the accuracy of the source-location estimate. The multiple mobile sensors work together, sharing their sensing data to achieve a collective perception, which fulfills gas dynamics and nonlinear characteristics. A crucial challenge in collective sensing is experimentation, as some gases are highly explosive, harmful, and toxic, making testing highly dangerous. Gas-sensing approaches cannot neglect these physical aspects without significant simplification.

This work proposes a novel behavior for *collective sensing* of gas leaks and source prediction in a *cyber–physical system* (CPS). The approach employs centimeter-scale mobile sensors to sense gas disturbances in industrial facilities. A group of mobile sensors is adopted for gas sensing, always searching for the source of leakage. The mobile sensors interchange information to achieve collective sensing, where each robot makes its decision of autonomous motion based on the perception of the whole group. Mobile sensors have autonomous behavior that is bio-inspired by bacteria that continually seek energy sources. The proposed approach is evaluated in a CPS, where a virtual gas and sensors are introduced to allow several experiments without risks. The dynamic gas behavior is specially designed to represent realistic behavior without losing any critical feature.

The remainder of this paper is organized as follows. Section 2 presents related works that address the challenges to be overcome through defined objectives. In this section, based on the research published in this area, the methods and techniques used in this study are compared to those in other works. In Section 3, a theoretical approach to all the elements involved in this work is adopted. The objects developed for applications and the creation of an experimental environment are detailed. Section 4 presents the details of the experimentation and all procedures designed for further evaluation. In section 5, the results obtained after exhaustive conducting different experiments are presented and discussed. This section also reports the conclusions and future perspectives of this work.

II. Related Works

Industrial environments generally have several risks involving all their sectors, among which threats can be highlighted, physical, ergonomic, mechanical, chemical, and biological. One way to minimize these risks is to use monitoring systems to measure harmful agents to people and equipment's physical integrity. Thus, sensors can be widely used to perform this type of monitoring, as presented in [4]–[6], where it is possible to verify the application of different kinds of sensors in different scenarios. One application of this work concerns the monitoring of gas in indoor environments as it involves significant risk in industrial, corporate, and residential environments. One way of making such measurements is to install fixed sensors dependent on the gas to arrive and sensitize the analysis. As presented in [7], different experiments were performed with a 3D grid and MOX sensors to visualize the temporal evolution of the gas distribution. Specific locations were chosen in an office room, including variations in height, release rate, and airflow.

Gas searching through fixed sensors can often be inefficient considering that it is dependent on airflow occurrence, which may result in undetected gas particles. Another important aspect is that even with an increase in the measurement points, the only solution to end the gas leak is detecting its source. The installation of multiple sensors allows only an extrapolation and estimation of the gas source location, as carried out in [8], which does not guarantee the source's actual position. Gas monitoring systems made up of fixed sensors require the gas to reach one sensor for leakage identification. Thus, there is no guarantee that a gas leak will be detected due to random factors such as wind speed, pressure in the environment, etc. The use of mobile sensors for gas detection increases the chances that measurements will occur, streamlines identification, and allows for faster corrective actions.

Monitoring and searching for gas sources associated with mobile robots is challenging and correlates with several research areas; as in [9], a series of existing robotic odor localization methods involving simulated and practical experiments are raised. Another example, [10] discussed a collaborative mobile sensing algorithm for distributed robotic networks to build scalar field maps. A control law embedded in the robots is proposed to avoid collisions during the robot' s displacement. However, the results are focused on simulations, taking into account theoretical models of sensing, locomotion, communication, and energy consumption. Several essential features are neglected, such as the system's scalability and the optimized measure of the necessary range of communication between the robots. In [11], a mobile robot equipped with a gas sensor is used to detect a gas source. However, the method performs path planning using historical wind data in the region in question. The evaluation consisted of correcting the trajectory in case any disturbance in the wind flow occurred. The method focuses on knowledge environments and is limited to a single robot. These approaches have several limitations because they depend on environmental knowledge to execute path planning. Gas leakage has dynamic and non-linear behavior and cannot be interpreted as a static dispersion without losing critical features.

An alternative is the adoption of autonomous behaviors that introduce the independence of the mobile sensor to achieve a specific objective, such as established in [12], where the importance and development of chemical robotic sensing is highlighted in the last decades, which has one of the fundamental capabilities of this work, which is the possibility of tracing chemical plumes to find its source. Several solutions to autonomous behavior were inspired by observing nature. Within the scope of robotic systems, there are numerous examples of inspiration in acuteness, such as for methods of control, movement, organization, communication, architecture, and individual or collective behavior, as presented in [13]–[20]. This kind of behavior is promising because it is not limited to following Cartesian coordinates or reactive obstacle avoidance but introduces several dynamic behaviors that allow the agents to adapt to different situations to achieve their objectives.

The gas-leak search requires a level of autonomy that enables mobile sensors to interact with the environment, always converging to a more gas-concentrated area. In [3], mobile robots equipped with gas sensors are used to find gas sources from the gas diffusion model using differential equations, using a probabilistic approach to source identification. The results show that mobile robots explore the same locations during the search process. They do not work by collectively transmitting information between the multi-sensor system, which introduces delays in detection and increases the risk of accidents. An approach that analyzes different search algorithms for the gas source is presented in [21]. Mobile robots with humidity sensors were used to detect the dispersion of moisture in an environment. A moist air source replaced the source of gas to preserve the people who worked in this laboratory. Promising results in the search for a humid air source were achieved, but the mobile robots adopted in the experiments did not work collectively, each being independent of the other. Thus, the scalability increases the agent's number, but not the gas-sensing capability, until a significant number of agents will degenerate the search because of excessive collision avoidance.

The search for greater concentration is the basic concept developed in this work. The behavior was bio-inspired in the analysis after studies related to the observation of bacteria, whose main objective is to detect and move to regions where there are food sources while avoiding dangerous regions for its survival. In biology, this behavior is known as *Chemotaxis*, such as presented in [22].

This paper aims to propose an approach of a group of mobile sensors that exchange information to achieve collective sensing, moving autonomously in the environment through a bio-inspired behavior, and continuously looking for areas with a higher concentration of gas. The decisions of intelligent behavior consider collective sensing to optimize the gas-source search. This work's major contributions are highlighted in the areas of the centralized multi-robot approach in a semi-unknown environment. The novel aspects can be enumerated as

- collective decision-making;
- communication mechanism to multi-robot systems;
- and a cyber-physical system for collective gas sensing.

III. Collective Gas-Sensing Approach

In this work, collective sensing was adopted to ensure an optimal gas-source search, minimize costs, and avoid potential risks. The dynamic distribution of mobile sensors enables adaptation to the nonlinear behavior of the gas dispersion.

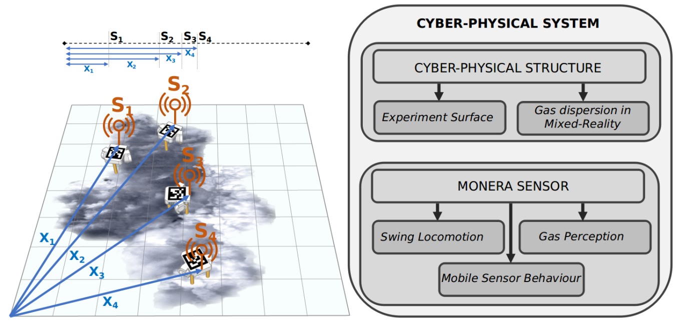

Fig. 1. Overview of collective gas sensing approach.

In this scenario, the proposed method of collective sensing is illustrated in Figure 1, where the approach is organized into two main blocks. The CPS corresponds to all the mechanical parts planned and developed to integrate mobile sensors with virtual elements. An essential element is the surface of the experiment, where all virtual and real components are integrated through mixed reality.

Another crucial part is the dispersion of gas (a cyber element) that expands in the environment with a dynamic behavior regulated by several parameters. The *monera* mobile sensor (i.e., robot) is interconnected with two-dimensional exploratory capability. It was specially designed with low-cost components to have small dimensions, thereby facilitating laboratory experiments. The mobile sensor autonomy depends on its olfaction, where the robot continually feels gas and moves to areas with more gas concentration, as illustrated in Figure 1. Collectivity is present in the interaction between mobile sensors, as they all share their data to achieve the primary purpose of finding the gas source.

A. Bio-Inspired Autonomy

The mobile sensors are designed with autonomous behavior that allows distributed decisions to search for a source. The proposed approach is based on the behavior that bacteria have to define survival actions. The cognitive mechanisms of these beings were explored to inspire the behavior of mobile sensors. This approach involves programming the mobile sensors to move similarly to bacteria, developing *chemotaxis* behavior, where each sensor *feels* the environment. For example, bacteria are attracted to food and avoid regions where antibiotics are detected.

Figure 2 shows the real behavior of *chemotaxis* of a bacterial colony [23]. In images (a) and (b), the bacterial colony has a specific direction. When food is detected, the direction changes, as observed in images (c) and (d). It is possible to observe that sudden changes in direction occur when the bacterial colony detects a food source. In this way, the bio-inspired behavior employs these principles to ensure an autonomous search for food, i.e., the gas. Thus, mobile sensors always look for regions with more food offerings (i.e., greater gas concentration).

This principle is used throughout the experiments because the repulsion mechanisms that bacteria have for antibiotics are implemented to prevent mobile sensors from coming into contact with undue regions. This is also implemented to find

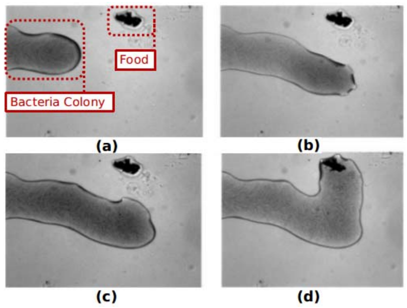

Fig. 2. Motion of bacterial colony [23]. (a) Initial displacement of the bacterial colony. (b) Search for the colony's energy source. (c) Detection and change of direction of the colony. (d) Energy source reached.

the gas source, as the *sensor* tests the air and directs its movements to the highest concentration, similar to what bacteria do to find food. In addition, repulsion among bacteria is also exploited when experiments involving collective behavior are tested.

The biological inspiration is related to food attraction and other batteries' repulsion. Each bacteria is able to navigate in the environment independently but considering the perception of the whole group. Sensors used in the experiments can navigate different paths, even with the collective behavior because not have any coordination restriction.

In the flowchart in Figure 3, it is possible to verify the bio-inspired behavior in all stages. Because all gas measurements correspond to the mobile sensor constantly feeling the environment, each sensor reading corresponds to the constant search for the gas source, as with bacteria in nature. The behavior to avoid dangerous regions is verified in the *Collective Sensing blocks*. During the exchange of position and trajectory information among mobile sensors, minimum distances are established such that the mobile sensors between these points and each sensor's current position are established.

B. Collective Sensing

The search for a gas source is based on continuous reading of the gas measurement in real time compared to the last reading time. If the difference between readings is less than zero, the mobile sensor continues in that direction. Otherwise, it rotates 90° clockwise or counterclockwise, depending on each sensor's position in the environment. The flowchart in Figure 3 exemplifies the adopted algorithm, where M_N is the measurement of the gas concentration at time N, and M_S the concentration value measured in the region of the gas source. An essential characteristic for the analysis of concentrations is related to their values because the lower the values of M and RS/R0, the higher the gas concentration.

The behavior of *collective sensing* restricts the exploration of the gas concentration to unexplored regions. Therefore, the shared data of the mobile sensors' trajectory history determines the decision-making process related to the direction that the mobile sensors should take. Thus, collisions between them and regions explored repeatedly are avoided. This collective behavior is highlighted by red dots in Figure 3, when this part of the collective sensing is not activated, the gas source search becomes an individual search. With this, the risks of collisions

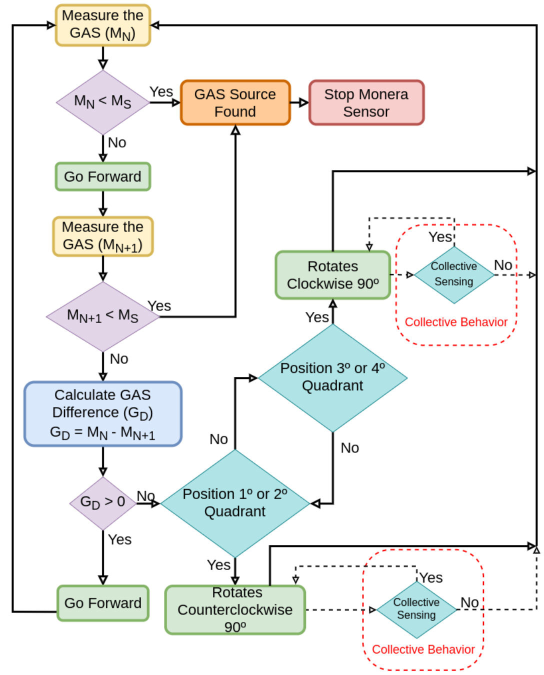

Fig. 3. Flowchart of seeking of the gas source.

between mobile sensors are highlighted. Both aspects are addressed in the experimentation section of this work.

All gas-concentration sensors work with the RS/R0 ratio (a dimensionless value). The values shown in Figure 3 correspond to this ratio, were RS is the sensor resistance and R0 is the sensor resistance in fresh air. This relationship shows the gas concentration. Finally, one premise of this paper refers to the already known value of the M_S gas source concentration.

IV. Cyber-Physical System

The section relates to the infrastructure of experimentation, where all elements (cyber and physical) are mixed in the same environment. Reality fusion is achieved through an RGB camera fixed at the top of the structure. The camera is attached to an adjustable metallic structure, which allows variation and mobility as needed. These adaptations will enable an increase in the degree of freedom of the structure, as there are angular and linear adjustments shown in Figure 4.

An articulated arm allows the adjustment and support of the upper camera, which is also responsible for the localization of *monera* sensors in the environment. A side RGB camera is employed to capture the perspective view of mixed-reality. The two cameras have a maximum resolution of 1080 × 720 at 30 frames per second (fps).

A. Experiment Surface

The experimental surface is a physical layer designed in glass and wood. The function of the glass is to support the accompanying structures of mobile sensors, which allows the mobile sensors to move in all directions with the least possible friction between these low-cost and easily accessible materials. The dimensions of this surface are 4 mm × 400 mm × 500 mm (thickness × width × length). Wood is used to fix the

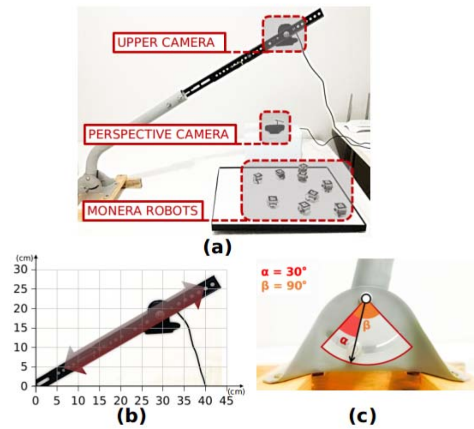

Fig. 4. (a) Structure overview; (b) camera variations and linear adjustments: minimum point [50, 30] and maximum point [400, 250], units in milimeters; (c) angular adjustment [0° - 90°].

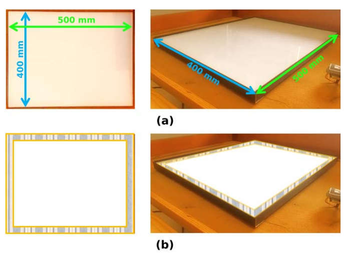

Fig. 5. *Experiment Surface*. (a) dimensions; (b) safety area.

adjustable metal arm and support the glass. All components are incorporated in a metallic frame, increasing their resistance. Under the glass, a layer of opaque white paper is placed that provides contrast for reading AR-tags (a fiducial marker system to support augmented reality) located on top of the mobile sensors used for localization. The surface is shown in Figure 5.

The presented system assists in experimentation of gas-source search techniques, which is why simple components such as cameras were used, but nothing prevents this system from being suitable for utilization in real environments.

B. Gas Dispersion in Mixed-Reality

The mixed-reality coupling between a virtual gas source and dispersion with real elements is performed. For this, the physical dimensions of the real world (surface of the experiment) must exactly correlate with those of the virtual world (gas dispersion and gas sensors). Figure 6 shows an overview of the cyber–physical environment, and details of the three environments (real, virtual, and mixed reality) used to implement this system. The virtual walls and windows were hidden during the experiments to make the processing less bulky, but all their influence was active.

The compatibility between virtual and real environments allows the dispersion of virtual gas to be adequate for the size of the experimental surface. It was also established as a virtual anchor to attach cyber-sensors on top of mobile sensors.

Gas dispersion is a crucial feature of collective gas sensing, where it is not possible to neglect any dynamic feature without loss. The cyber–physical approach is based on the creation of virtual gas dispersion to safety requirements and ease of

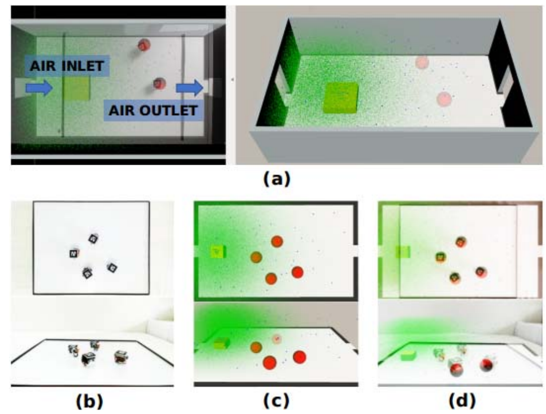

Fig. 6. (a) Experiments' components: virtual gas, virtual walls, virtual air inlet and outlet, virtual sensors, and real robots; (b) Physical elements; (c) Cyber elements; (d) Cyber-Physical System.

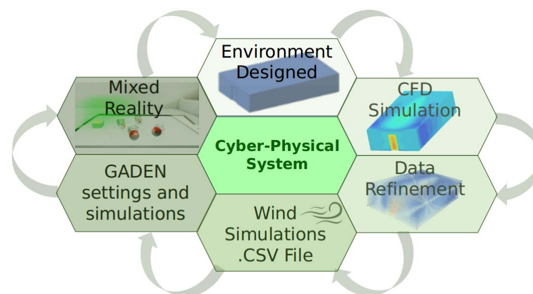

Fig. 7. Steps for developing the virtual system.

experimentation. The gas conception adopts the technique of [24] to 3D gas dispersion simulator in realistic environments (GADEN). This method allows the simulation of complex 3D gas dispersion through the reproduction of real wind tunnel experiments formulated in computational models of gas dispersion.

In addition to parameter specifications, several designs of dynamic behavior must be performed to allow realistic 3D dispersion of gas. These steps are summarized in Figure 7.

The first step comes down to the graphic development of the environment (internal and external) in which the experiments will be developed. Subsequently, the internal environment (volume) is used to generate the dynamics of particles in the environment through *Computational fluid dynamics* (CFD). Bearing in mind that GADEN needs a perfect 3D points grid, a post-processing of the data is performed. With this, it is possible to guarantee that the cell size is uniform. This refined data set is used in GADEN, together with the previously developed graphical environment. Thus, it is possible to join the simulated environment with the real robots through the Robot Operating System (ROS), obtaining the complete cyber-physical system.

C. The Monera

The mobile sensor, *monera*, is specially designed to be small with a height, width, and length of 37 mm $\times$ 42 mm $\times$ 35 mm, respectively. Another premise of the project is that it must be built with traditional components, easily assembled, and low cost. The robot hardware was designed using two cards. The

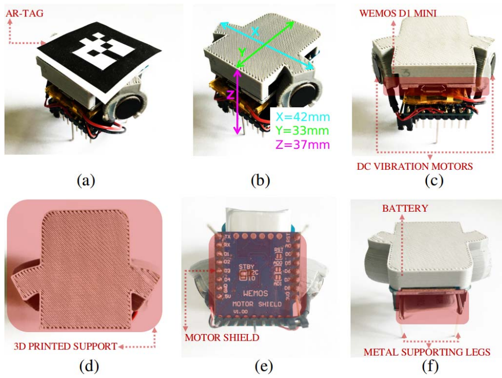

Fig. 8. Dimensions and elements of *monera* sensor. (a) AR-TAG. (b) Dimensions of the sensor monitor. (c) Control board and vibration motors. (d) Support for AR-TAG and vibration motors. (e) Motor shield. (f) Battery and metallic support of the sensor monera.

first, *Wemos D1 mini Pro Wi-Fi*, contains the microcontroller along with *input* and *output* ports, a communication port, a *Wi-Fi* transmission element, an integrated antenna, and 16 MB of flash memory. The second board is a *Wemos motor shield*, which is capable of controlling up to two DC motors via the *Wi-Fi* network and its *Wemos D1 Mini board*. The DC vibratory motors that the shield controls require a maximum voltage of 15 V, with a maximum current of 1.2 A (absolute maximum ratings).

Through their pins, they connect the two plates of the *monera*. Two DC vibrating motors are required to propel and move the robot. A 400-mAh LiPO battery is responsible for powering the entire system, and a 3D-printed part supports the DC motors, as shown in Figure 8.

Robot locomotion is based on differential vibration, which promotes a controlled swing to change directions and moves forward. Similar to the principles adopted in Kilobot presented in [25], where the motors are activated via pulse-width modulation (PWM), which establish different levels of vibration and subsequently speed for the robot. When the robot moves in a straight line, both motors are activated alternately. When clockwise movement is needed, the left motor is activated, and when the motion must be counterclockwise, the right motor is activated. Figure 9 shows the drives of the actuators in their respective directions.

The swing locomotion allows clockwise and counterclockwise movements to always rotate on the same support base. This characteristic was fundamental in dealing with the forward movement of the robot due to the alternate clockwise and counterclockwise movement at suitable intervals. Figure 9 **(c)** shows the result of this displacement.

D. Gas Perception

The *monera* sensor has an AR tag to identify its ID. The AR tag is the most appropriate way to implement coupling between real and virtual features. This element is also responsible for providing data that is used to give the sensor's position, interact with the environment, and implement a control system.

There are several types and models of sensors used to monitor different types of gases. Some are sensitive to carbon

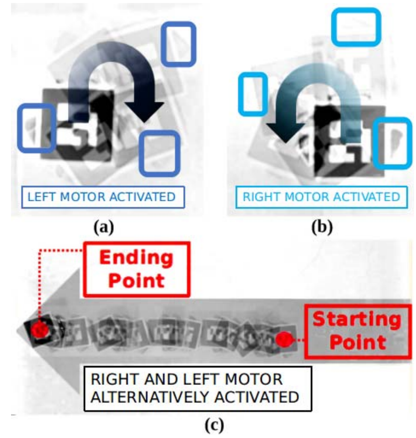

Fig. 9. (a) The ***Clockwise*** movement requires only the activation of the left motor. (b) The ***Counterclockwise*** movement requires only the activation of the left motor. (c) The ***Forward*** movement requires alternating activation and deactivation between the left and right motors.

monoxide, methane, ethanol, acetone, and hydrogen, among others. The sensor used in this work is a *metal–oxide semiconductor* (MOX) *TGS2600*. The sensor operates via the constitution of the sensor element by a semiconductor layer of metal oxide formed on an alumina substrate of a sensor chip together with an integrated heater. When a gas is detected, the conductivity of the sensor increases according to the concentration of gas in air. Thus, an electrical circuit can convert the change in conductivity into an output signal that corresponds to the gas concentration [26].

An essential feature of the TGS 2600 is that it is highly sensitive to low concentrations of gaseous contaminants. As presented in [27], the sensor has applications in monitoring indoor air quality and air-cleaner control. In addition, it stands out for having low energy consumption, long life, and low cost. The miniaturization of the sensor chip, TGS2600, requires a heating current of only 42 mA [26].

In GADEN development, the modeling of the TGS2600 used the manufacturer's data-sheet to estimate the RS/R0 resistance ratio from the truth concentration provided by the simulator. Subsequently, a low-pass filter was applied to simulate the rise and decay response times [24], 4.8 and 18.75 seconds, respectively, for the TGS2600. Finally, RS was estimated at time given the reference resistance R0 equal to 50 kOhms.

After presenting the main concepts and technologies covered in this work, it is possible to summarize in an objective way that the problem is to develop a simple system, but that has real aspects reducing the gap between simulation and implementation is authentic systems. The proposed approach allows different gas-sensing techniques to be tested thoroughly. Thus, the experiments covered in the next section demonstrate the possibilities that this system can provide in collective sensing.

V. Experimental Evaluation

The method used to test and prove the proposed approach of collective gas sensing is through experiments with a complete

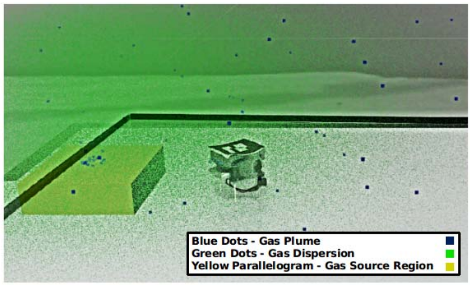

Fig. 10. Demonstration of gas source search in the CPS.

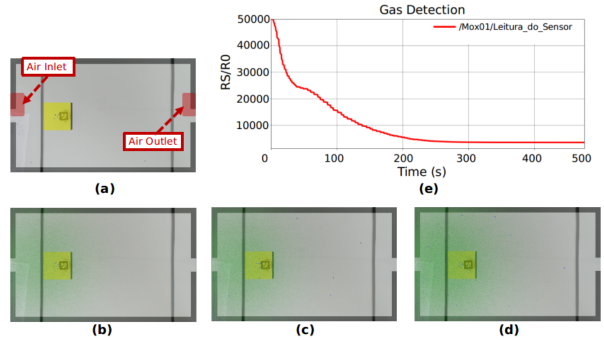

Fig. 11. (a) Air inlet and outlet indication. (b), (c) and (d) They present different levels of gas concentration at different time points. (e) Graph corresponding to the search for the gas source of the experiment shown in Figure.

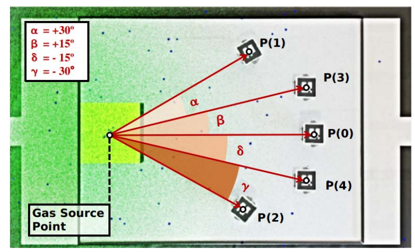

Fig. 12. Arrangement of *monera* sensors. P(0), P(1), P(2), P(3), and P(4) are the possible initial positions defined in this paper for the experiments.

cyber–physical environment. Thus, three methods are applied, the first using a mobile sensor to find the gas source, whose objective is to evaluate and prove that the presented methodology is functional for this type of application. The second approach uses five independent mobile sensors to increase the system's complexity, observe possible gains, and increase the resulting efficiency. Finally, the third approach will handles experiments involving collective sensing so that the results can be compared with those of the second approach.

A. Demonstration of the CPS

The experiment consists of exposing the mobile sensors to an environment where there is already a gas leak and observing the trajectory made by the mobile sensor to find the gas source. The objectives of this experiment are to understand the interaction and integration of all elements of CPS, present the *swing locomotion* in a practical experiment, and understand the variation of the gas concentration. Figure 10 presents a perspective image with all elements.

Gas concentration data are collected and used to control the robot in search of the gas source. The starting position of the mobile sensor was [181, −114] mm. The angle between the source and sensor is 23°, and its orientation is 60°. According to the CFD simulation, these blue dots represent a gas plume with a mathematical model detailed in [24], and green dots represent gas dispersion. The yellow parallelogram was used to highlight the region with the highest gas concentration, and its center, coordinates [−201, 32] (mm), is the exact point of the gas source. Figure 11 shows the gas concentration detected until the mobile sensor finished the task. Again, it should be noted that the lower the values of M and RS/R0, the higher the gas concentration.

The experimental environment was designed by a closed room (similar to an industry) with an external air inlet and outlet. A unique gas source specified in the middle of the yellow parallelogram starts to leak gas. The gas dispersion behavior is dynamic, considering the particle characteristics and the external airflow. However, the gas leak is more rapid than the intrusion of external air, leading to a massive gas dispersion in the environment.

B. Accuracy Evaluation

Collective gas sensing is evaluated in a set of experiments aimed at the multi-search of the gas source. Thirty-five experiments with different levels of complexity and arrangement were developed. The experiments involve releasing the autonomous mobile sensors in the environment with gas dispersion, observing their autonomous and bio-inspired behavior, and analyzing their route to the gas source region. The mobile sensors have independent behaviors, and collective behaviors are not associated with these experiments. The initial positions of the mobile sensors vary between the options represented in Figure 12.

All trajectories performed by the mobile sensors are stored during the search for the gas source, as shown in Figure 13, through an example carried out in the third experiment. These data are later used for path analysis and validation of the bio-inspired algorithm.

Several data were collected for performance analysis of the search algorithm for the gas source throughout the experiments. One of the data types represents the distance traveled by the agents to the gas source region's meeting. These data are presented in Figure 14, where the numbers of the experiments are quantified, as well as the number of mobile sensors and the distance covered.

Throughout the experiments, some critical questions are verified. During the experiments with one, two, and three mobile sensors, all sensors managed to reach the gas source, thus carrying out their requested task. In experiments with four and five mobile sensors, a gradual decrease in efficiency was observed in performance, highlighted in red in Figure 14. Another interesting point of analysis refers to the system's scalability: the appropriate number of mobile sensors

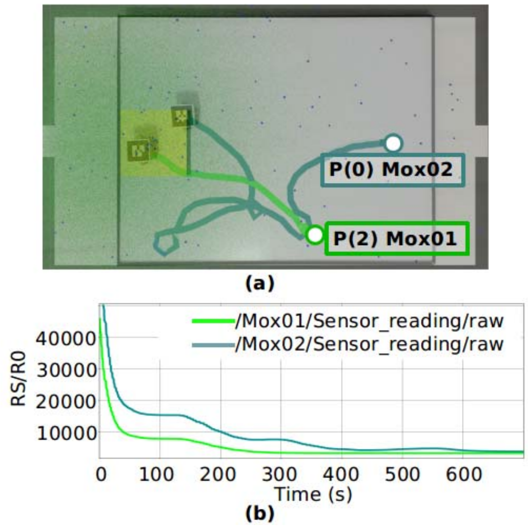

Fig. 13. Behavior of the experiment 3; (a) Trajectory of the mobile sensors (Mox01 and Mox02) until they find the gas source; (b) Changes in gas concentration over time.

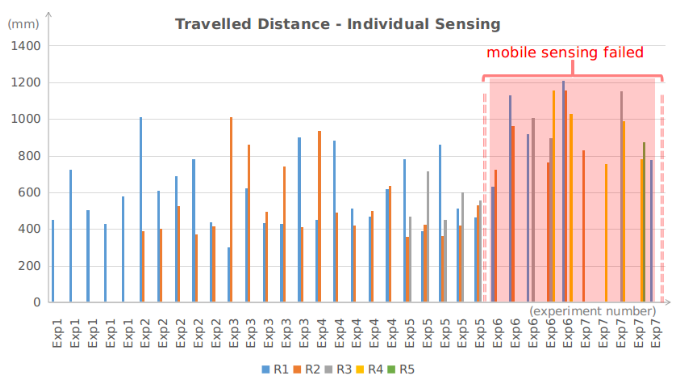

Fig. 14. Distance traveled by the mobile sensors in each experiment performed. R1, R2, R3, R4, and R5 correspond to mobile sensors 1, 2, 3, 4, and 5, respectively.

for exploration of the area. This information is shown in Figure 15.

C. Evaluation of Collective Behavior

Collective sensing has several possibilities for application. In this work, the collective concept is linked to an action based on another agent. That is, the position data of the mobile sensors will be shared among all agents.

Thus, the gas-search algorithm has been improved. The deviation in sensor trajectories corresponds to the implemented collective characteristic, avoiding repeated explorations in different spaces in the environment. For example, in addition to the search behavior for the highest gas concentration, when a sensor detects a location or trajectory traveled by another sensor, the rotation direction is decided considering the agents' global positions. This is in contrast with the flowchart shown in Figure 3, which is based only on the individual sensors' gas concentrations.

The coordinates of the sensors are sent to a central processing unit that manages all this information. Thus, point

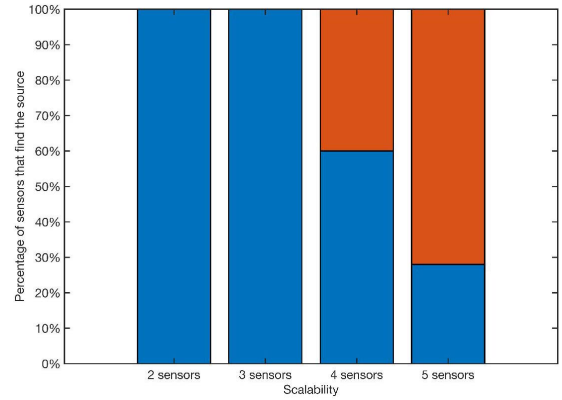

Fig. 15. Analysis of the system's scalability through the sensors' individual approach, that is, without the collective behavior. The red part in the histogram corresponds to the percentage of robots that have not found the gas source.

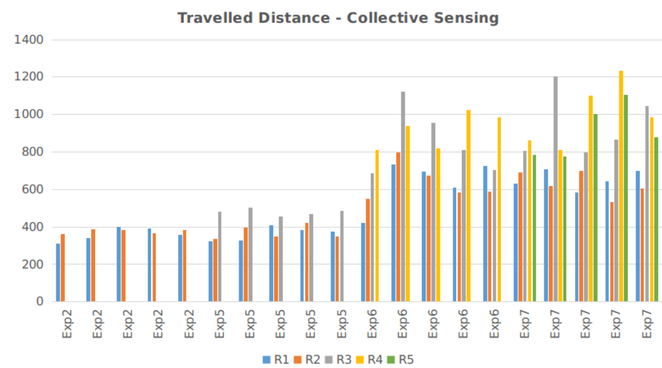

Fig. 16. Distance traveled by each mobile sensor in the collective approach. R1, R2, R3, R4, and R5 correspond to mobile sensors 1, 2, 3, 4, and 5, respectively.

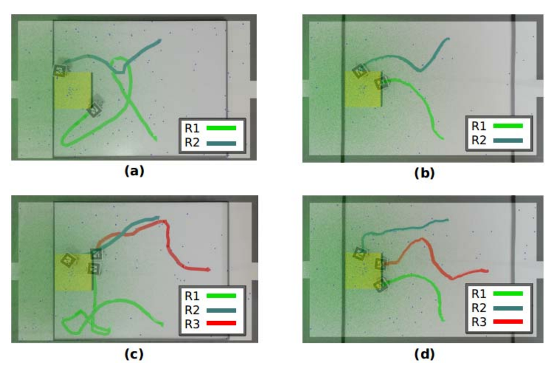

Fig. 17. Trajectories traveled by mobile sensors (R1, R2, and R3) with different approaches. Images (a) and (c) correspond to individual sensing and images (b) and (d) to collective sensing.

matrices are created containing the coordinates of the trajectories of each mobile sensor. As the sensors move, their distances are checked, and if any distance between the *mobile sensor* and *trajectory* is less than 40 mm, a deviation is made, preventing areas from being explored more than once. Twenty experiments were performed considering the collective approach. Experiment one was not mentioned, as it is not possible to verify collectivity with just one agent. Experiments

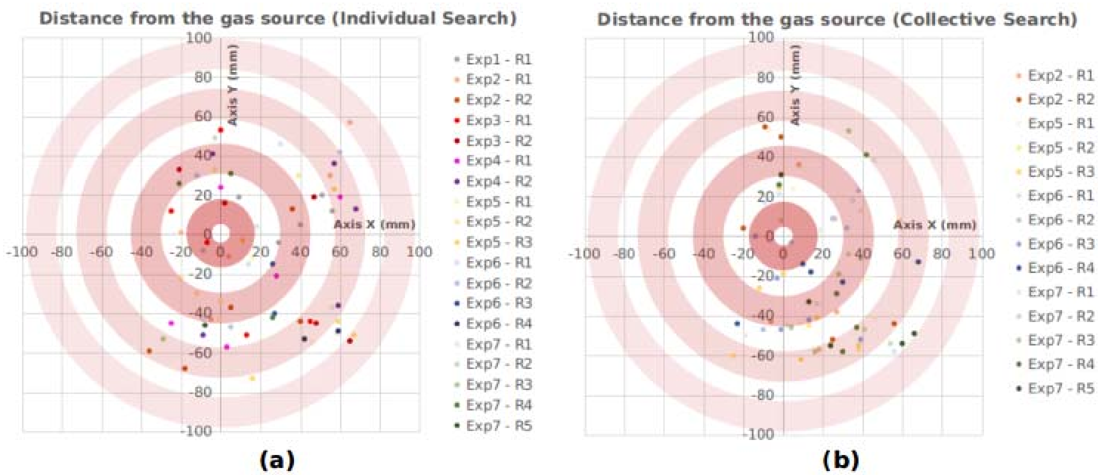

Fig. 18. Final positions of the mobile sensors after carrying out experiments. (a) Individual sensing. (b) Collective sensing. R1, R2, R3, R4, and R5 correspond to mobile sensors 1, 2, 3, 4, and 5, respectively.

two, three, and four, on the other hand, were tested using two mobile sensors, but as their results in the individual approach were very similar, it was decided to redo only one of them, Experiment 2. Finally, experiments five, six, and seven were completely redone. Figure 16 shows the distances traveled by the mobile sensors considering the collective approach.

Some critical issues are noted, such as completing the task by all the mobile sensors reaching the gas source. In addition, one notices that the appropriate number of sensors for exploration in the space considered is three, because when this number was increased, a substantial increase in the distance covered was obtained.

The optimal number of mobile sensors for exploration in the considered environment is three. The increment in this number results in a substantial increase in the distance covered due to environment size restrictions. In these situations, an excessive collision avoidance (or activation of repulsion mechanism) is adopted.

D. Comparisons Between Individual and Collective Approaches

After surveying the different approaches' results, the main results were compiled and compared, aiming to highlight some contributions of the work. First, as shown in Figure 17, it is possible to verify that mobile sensors do not explore places already visited by other sensors, making the collaborative approach more efficient at this point, as there is no redundant energy expenditure by location.

Another essential point to be presented is the different arrangements defined for carrying out the experiments. This information is summarized in Table I. The choice of starting positions aims to provide exploration in different points of the environment. The locations of positions P (0), P (1), P (2), P (3), and P (4) can also be seen in Figure 12.

One of the fundamental analyses to be carried out in this work is related to comparing independent and collective mobile sensing. For this, the variables corresponding to the distance covered and the mobile sensors' *final positions* were

TABLE I
ARRANGEMENT OF THE EXPERIMENTS

Individual Search		
Exp (x)	**Number of mobile sensors**	**Initial position**
1	1	P(0)
2	2	P(1), P(2)
3	2	P(0), P(1)
4	2	P(0), P(2)
5	3	P(0), P(1), P(2)
6	4	P(1), P(2), P(3), P(4)
7	5	P(0), P(1), P(2), P(3), P(4)
Collective Search		
Exp (x)	**Number of mobile sensors**	**Initial position**
2	2	P(1), P(2)
5	3	P(0), P(1), P(2)
6	4	P(1), P(2), P(3), P(4)
7	5	P(0), P(1), P(2), P(3), P(4)

compared. In Figure 18, it is possible to observe the results. Between the approaches, the average distance between the gas source and the mobile sensors' final position decreased by 6.2%.

One of the most important results of this work, which corroborates with the researchers' expectations, is that the collective approach improves the system's efficiency with a reduction shown in Figure 19 in the trajectory traveled by the mobile sensors. Another significant result to be highlighted is the scalability of the system in both the individual and the collective approach. In both cases, the appropriate number of mobile sensors for this type of experiment was three agents. Even in the collective approach, where all the mobile sensors managed to reach the gas source, there was an exacerbated increase in the trajectory they traveled.

Table II summarizes the results of the experiments regarding the standard deviation and the averages of the mobile sensors' distances. The first column indicates the number of mobile sensors. The second and third columns enumerate the averages of the distances traveled (in millimeters) by the sensors. Finally, the fourth and fifth columns list the standard deviations of the distances covered (in millimeters) until the gas source is reached. It is important to note that only samples of experiments from the sensors that could complete their task were used.

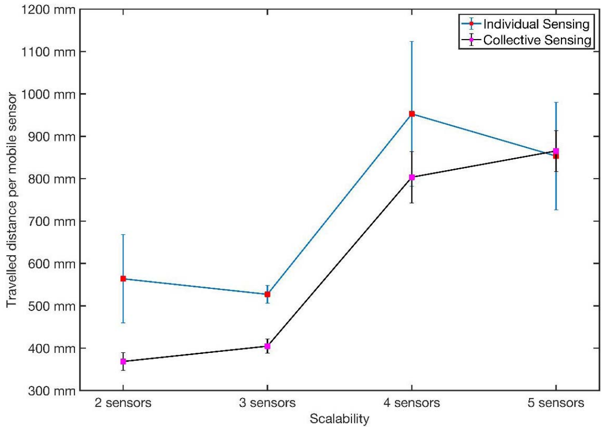

Fig. 19. Comparison between the distance covered between the individual and collective sensing approaches.

TABLE II
RESULTS OF THE INDIVIDUAL AND COLLECTIVE APPROACH

Sens.	**AVG.** ***Ind.***	**AVG.** ***Col.***	**Std. Dev.** ***Ind.***	**Std. Dev.** ***Col.***
1	536.8	-	106.3	-
2	563.7	368.6	123.0	22.0
3	527.1	404.8	114.5	27.9
4	980.6	762.2	129.6	114.0
5	896.2	827.5	105.3	109.3

VI. CONCLUSION

This paper presented a new approach for *collective sensing* applications introducing the *cyber–physical system*. This approach can be applied for several purposes, such as collective monitoring or mapping gas in different environments. A semi-physical experimental system is a method that is available to integer physical and virtual elements.

The mobile sensors search for the gas and move autonomously, bio-inspired in bacteria's behavior, where survival is their primary goal. In the case of mobile sensors, they must find their "food" (gas source), always avoid contact with antibiotics (structure limits), and, during collective behavior, avoid other mobile sensors. Locomotion through a swinging motion allows the gas levels to be scanned. Small variations in the friction coefficient between the mobile sensors and the experimental surface can alter the trajectory, leading to higher paths traveled until the gas source met. Differences in the battery level of the robots were analyzed during the experiments, and different travel distances were observed during the tests. The dynamic gas behavior and calibration (rectilinear movement, clockwise rotation, and counterclockwise rotation) of the mobile sensors are compatible with the battery level. During the discharge process, the response of the motions changed.

Another side of the analysis is related to the improvement in collective work between mobile sensors achieved, with efficiency in exploration being the most notorious issue. Another necessary verification is that of the ideal number of robots in each type of experiment. When an individual's behavior is altered experimentally, the three is the maximum number of mobile sensors that arrive at the gas source. From that number (four and five) of mobile sensors, not all could reach the gas source region owing to their collisions and deviations in the trajectory. Three was also the most suitable number in collective experiments, but in this case, the mobile sensors always arrived in the gas-source region. However, in the experiments with four and five mobile sensors, the robot's distance traveled was very long.

The results presented in this work indicate that the semi-physical experimental system can provide researchers with the opportunity to test different algorithms, arrangements, and configurations of cyber–physical systems in unhealthy environments. In addition, the results present data that indicate the ideal amounts of mobile sensors for the exploration and detection of gas leaks indoors. This scenario allows researchers in the collective sensing area to use the results presented as parameters for future work.

One approach to be considered in the future is testing with other gas sensor models, both virtual and real, to increase the complexity and flexibility of the proposed system.

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