Cooperative Pollution Source Exploration and Cleanup with a Bio-inspired Swarm Robot Aggregation

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Abstract. Using robots for exploration of extreme and hazardous environments has the potential to significantly improve human safety. For example, robotic solutions can be deployed to find the source of a chemical leakage and clean the contaminated area. This paper demonstrates a proof-of-concept bio-inspired exploration method using a swarm robotic system based on a combination of two bio-inspired behaviors: aggregation, and pheromone tracking. The main idea of the work presented is to follow pheromone trails to find the source of a chemical leakage and then carry out a decontamination task by aggregating at the critical zone. Using experiments conducted by a simulated model of a Mona robot, the effects of population size and robot speed on the ability of the swarm was evaluated in a decontamination task. The results indicate the feasibility of deploying robotic swarms in an exploration and cleaning task in an extreme environment.

Keywords: Swarm robotics · Aggregation · Bio-inspired · Exploration

1 Introduction

Exploration of extreme environments came to the focus of the robotic research community [15] since, as shown by the relatively recent Fukushima disaster, most standard robots fail to operate reliably in extreme environments with chemical and radiation contamination [23]. For instance, in multi-robot systems, wireless communication is widely used to transfer data between robots [13]. Radiation sources can hamper wireless connections, rendering standard multi-robot teams ineffective. To overcome this problem, one can use short-range communication

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techniques, common in robotic swarm research, such as an effective inter-robot connection protocol [17], which is more resilient to extreme conditions.

In the multi-robot research community, researchers mainly tend to distribute the robot tasks among large numbers of simple robots rather than assigning a complex duty to a single robot because of the numerous advantages of multi-robot systems [6]. For instance, a group of cooperating robots can carry out a task at a higher speed when compared to a single robot [4]. A collective decision made by a group of robots will be more reliable than the decision of a single robot in most applications. In addition, multi-robot systems are more fault-tolerant, and improvements in efficiency can be achieved simply by scaling up the number of robots in the swarm. For example, sensor noise and uncertainties in extreme environments can heavily influence a single robot's decisions. On the other hand, a multi-robot platform can compensate for this uncertainty by processing and combining the information of multiple agents [10].

Moreover, emergent swarm behaviors [28] are also robust to noise and uncertainty of an individual robot's sensors. By having this point in mind, robot interaction rules and methods are required in order to establish a protocol by which a number of robots can cooperate with each other and complete a task. In many cases, such protocols contain high-level data transfer among robots and decision centers [8]. Bio-inspired behaviors shown by social animals like ants, bees, and termites can be utilized to establish social behavior among multiple robots [12]. The observation of effective behaviors in social animals encourages us to choose a deeper and detailed approach to apply a similar scenario for robots.

Aggregation is a behavior that is observed in many social animals varying from insects [7] to amoeba [26]. This behavior can be defined as the gathering of individuals around an area with optimal ecologic properties. By forming this aggregation, they gain new abilities like building a habitat, deterring much stronger predators, and defeating larger prey [24]. Aggregation is observed in two types: cue-based aggregation [20], in which nest members aggregate by following an external cue, and self-organized aggregation, where nest members aggregate without any external guidance and regardless of their environment. For exploration in extreme environments, physical cues (e.g., chemicals or radiation) are crucial; therefore, cue-based aggregation is more relevant.

The BEECLUST method, introduced in [27] is one of the most popular bio-inspired aggregation principles. By performing a detailed analysis of honeybees, which follow cue-based aggregation around a zone with a more optimal temperature [14], the BEECLUST aggregation method [27] was chosen as a basis to implement our exploration system. This bio-inspired aggregation was studied intensively in many research works [3,5].

In terms of communication challenges in swarm robotics, one of the most distinct phenomena of social insects' interactions is their communication method. Social insects often use the environment itself as a communication medium by spreading organic substances (pheromones) that can indicate a multitude of environmental features from the presence of food to dangerous animals. The interaction of pheromones and individual agents leads to efficient swarm behaviors capable of solving chaotic and complex situations. The principles of pheromone communication were utilized by swarm robots in various research studies [2,18,21], and its potential for robotic applications has been demonstrated. For instance, artificial pheromone trails were employed for aiding swarm aggregation in [22]. They proposed a state-of-the-art artificial pheromone system that could emulate environmental effects on pheromone distribution more than previous studies on simulating artificial pheromones. It was concluded that the emulation of realistic spatio-temporal development of pheromone trails brings new insights for the interaction of swarm members, environment, and released pheromones.

In this paper, a method for exploring environments with extreme conditions, e.g., chemical or radiation leakage, is developed using robot swarms. The proposed method combines the BEECLUST algorithm and pheromone following behavior. The main goal of this paper is to make robots detect and clean the source of chemical leakage in order to decontaminate an entire environment. In particular, we investigate the impact of population size, speed of motion, the intensity of environmental cues (contamination magnitude), and coherency of the group, on the efficiency of the cleaning operation.

The rest of the paper is organized as follows: in the second section, the proposed exploration method is described. In the third section, the robotic platform and experiments are demonstrated. In the fourth section, the results of the experiments are analyzed and discussed. Finally, in the last section, the paper is concluded, and future work on this exploration method is explained.

2 Localization and Cleanup Method

In the proposed localization method, a combination of cue-based aggregation [27] and pheromone following behavior [21] was developed (shown in Fig. 1). Robots tend to reach the source of leakage by following the intensity gradient of the cue (contamination magnitude). This chemotaxis behavior has been shown in nature e.g., ants foraging. The main goal is to reach the source and start the cleaning task with the presence of other robots. They stop their motion and start the cleaning task when they detect another robot. Therefore, robots are always in one of three stages: 1) follow a chemical gradient, 2) avoid walls, and 3) stop and clean. It should be mentioned that the states of the original BEECLUST method are: 1) move forward, 2) avoid walls, 3) stop and wait. Hence, as it is apparent from the comparison of the BEECLUST method and the proposed method, the first state of the BEECLUST method is replaced by going towards the center of cue. Besides, the cleaning task is added to the last state of the BEECLUST method.

In the proposed method, after a robot-robot collision occurs, robots wait for a while, depending on the cue intensity that they sense. During this waiting period, they clean the contamination beneath them. Details about cleaning are provided in the next section. When the waiting time is over, they continue their initial task i.e., following a chemical gradient. The duration of this cleaning time, w_s, relies on the cue's intensity, where robots find other robots. Hence, this cleaning time is calculated using the following equation:

$$w_s = w_{max} \frac{\bar{S_c}^2}{\bar{S_c}^2 + 25000}, \tag{1}$$

where w_{max} is the maximum waiting time and $\bar{S_c}$ is the average reading from left and right sensors, $\bar{S_c} = \frac{s_r + s_l}{2}$, $0 \leq \bar{S_c} \leq 255$.

When the waiting time is over, robots make a turn of θ degrees where θ is a random variable with uniform distribution in the range of [90° 180°] in both the clockwise and counter-clockwise directions. After the random turn, robots continue to follow the chemical gradient in order to reach its center.

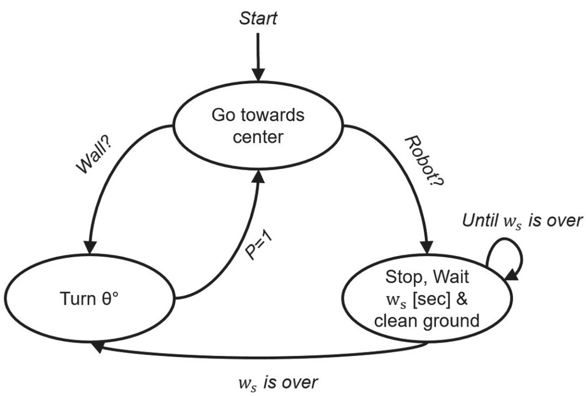
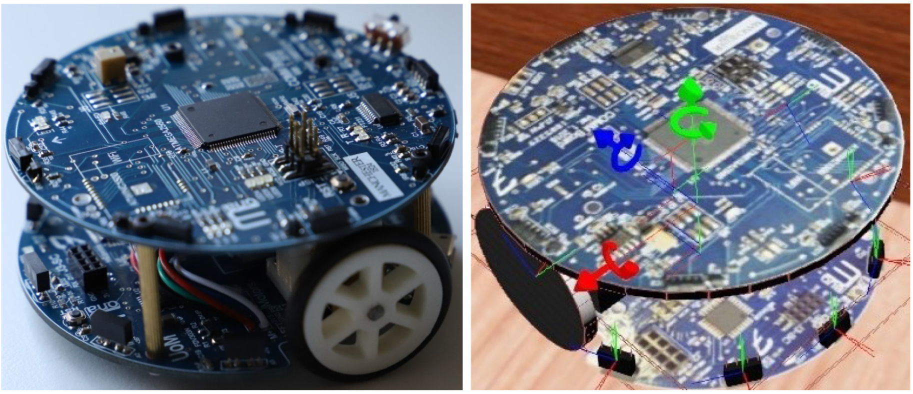


Fig. 1. Proposed exploration method. The ovals indicate stages and arrows indicate transitions.

3 Realization of the Method

3.1 Robotic Platform

The proposed exploration scenario was implemented using Mona robots [1]. It is a miniature wheeled robot with a diameter of 0.08 m. Mona was modeled [25] in Webots software to mimic the real Mona robot, and the proposed method was applied via a simulation model of Mona. Figure 2 shows the model used in Webots for Mona and the real Mona robot. IR proximity sensors are utilized in modeled Mona to detect collision and distinguish a wall from a robot. For robots to discriminate wall from other robots, when a collision occurs, each robot during collision sends an IR pulse to its neighbor. If the robot receives back an IR pulse from its neighbor, then it has collided with a robot. Otherwise, the collision has been made with a wall. This method of differentiating robots from wall was inspired by [27].



(a) (b)

Fig. 2. (a) Mona, an open-source low-cost robot developed for swarm robotics and (b) simulated model of Mona in Webots.

In order to sense the cue, as was mentioned previously, two sensors beneath the right and left wheels of robots are added. In the simulation, two sensors facing towards the ground were used, and after calibration, the value changes in the domain of [0 255] where 0 is a region with no chemical leakage, and 255 is the region with the maximum possible intensity of leakage.

To describe the algorithm by which robots follow the cue, two sensors are utilized under the left and right wheels of Mona in order to measure the cue intensity under these wheels. The value of these sensors are used in order to determine the desired rotation of Mona in a direction that cue increases so robots will move towards the zone with highest chemical leakage. To achieve this objective, required value of right wheel speed, N_r, and left wheel speed, N_l, were computed using the equations below:

$$N_l = \frac{s_l - s_r}{\alpha} + \beta \quad \text{and} \quad N_r = \frac{s_r - s_l}{\alpha} + \beta, \tag{2}$$

where s_l is the value extracted from the left cue sensor, and s_r is the value of the right sensor. The coefficient α adjusts the sensitivity of motors to the sensor values' difference in a way that with lower values of α robots will react dramatically to small differences between two sensors. In this paper, α is set to 2. The last parameter β is the biasing coefficient of motors with a possible range of [0 10]. For the modeled Mona, $\beta = 6$ is equal to speed of 0.08 ms^{-1} (speed of one Mona length per second) and consequently, $\beta = 3$ is equal to speed of 0.04 ms^{-1} (speed of half Mona length per second).

Interaction with Environment: To simulate the environment, a square shaped arena with the length of 2.85 m is considered which encompasses a circular shaped white region (contaminated zone) with a diameter of 2.227 m. The intensity of chemical leakage decreases linearly as it gets far from the center of

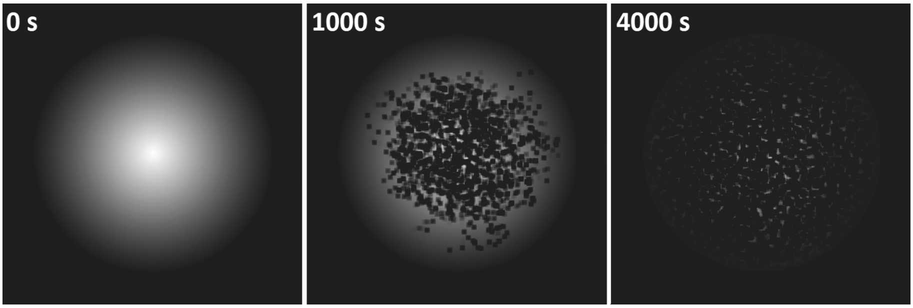


Fig. 3. Evolution of cue during 4000 s with $N = 30$ robots.

cue. Figure 3 shows the described cue at $t = 0$ s. To demonstrate the cleaning task in a greater details, the equation below is utilized while robots are in their waiting state:

$$\bar{S}_n = \bar{S}_c - (8 - \sqrt{p^2 + q^2}) \quad , \tag{3}$$

where $\bar{S}_c$ is the average value of cue measured by sensors, and $\bar{S}_n$ is the value of cue after cleaning. p and q are variables in a range of $[-4\ 4]$, and they were utilized to give gradient decrease shape to the cleaned area. As it is apparent, the cleaning level will have its maximum value of 8 per second when $p = 0$ and $q = 0$ so the center of the squared shaped cleaned region, will be darker and the cleaning level will have its minimum value of 2.34 per second when $|p| = |q| = 4$. Therefore, the outer layers will be cleaned less in comparison with the center. This equation will be executed once in a second while a robot is waiting. Figure 3 illustrates how a cleaned cue will look like in $t = 1000$ s and $t = 4000$ s.

3.2 Experimental Setup

Webots software is used to provide results for the proposed method, which is a simulation software for robotic platforms [19]. In Webots software, a supervisor is utilized to set initial conditions of robots and track simulation to record results. At the beginning of each simulation, robots are located randomly with uniform distribution by the supervisor. Also, they get random rotation with uniform distribution. The reason that the initial state of robots is randomized is to make results independent from robots' initial positions and rotations. Besides, random positioning of the initial state of robots is done with a different seed each time that simulation is repeated.

The effect of two parameters - speed of robot and population of the swarm - on the performance of the exploration are investigated. Experiments have conducted in five different population sizes of $N = \{10, 20, 30, 40, 50\}$ robots each one with two different speeds of a robot length per second ($v_r = 0.08\ \mathrm{ms}^{-1}$) and a half robot length per second ($v_r = 0.04\ \mathrm{ms}^{-1}$). Each set of experiments was repeated six times for the duration of 4000 s.

Table 1. Parameters and variables used in paper

Parameter	Description	Value/range
N	Number of robots	$\{10, 20, 30, 40, 50\}$ robots
v_r	Robot's linear velocity	$\{0.04, 0.08\}$ ms^{-1}
r_c	Radius of the cue center	0.7 m
t	Time of experiment	[0 4000] s
w_s	Waiting time of robots	[0 21.7] s
w_{max}	Maximum waiting time	30 s
s_r	Right sensor value	[0 255]
s_l	Left sensor value	[0 255]
N_r	Speed of right wheel	[0 10]
N_l	Speed of left wheel	[0 10]

Table 1 shows the list of parameters and variables that were used in this work. Three metrics were selected to evaluate the performance of robots: the change of average cue during the time, number of robots inside a circular zone with a radius of r_c, and finally, the coherency of robots. Additionally, to analyze the effect of the system parameters on each of the above-mentioned metrics, the ANOVA (Analysis of Variance) test was utilized, whose result will be presented subsequently. For each test, we have considered time, population, and the speed of robots as factors. In the following subsections, greater details about these three metrics is provided.

Average Cue vs Time: Average cue intensity is measured once in a second, hence by considering the overall experiment duration, 4000 samples of cue level are collected in each test case, and the median of measured cue intensities are used for six experiments in order to evaluate the swarm performance. The primary purpose of this measurement was to determine the impact of change in population size on the performance of robots. Besides the population size, the effect of robot speed on the overall performance is also studied.

Ratio of Robots Close to Cue Center: The ratio of robots that are within a circle with same center as cue and with radius of $r_c = 0.7$ m is computed each second for $N = \{10, 30, 50\}$ robots and $v_r = 0.08$ ms^{-1} in order to evaluate the performance of robots. Also, the cleaning pattern of robots can be recognized by this metric.

Coherency: The average distance of robots from each other is calculated to evaluate coherency for three populations with equal speeds. This observation is to figure out how much robots' behavior depends on each other during the experiments. Coherency also measures the level of cooperation among robots.

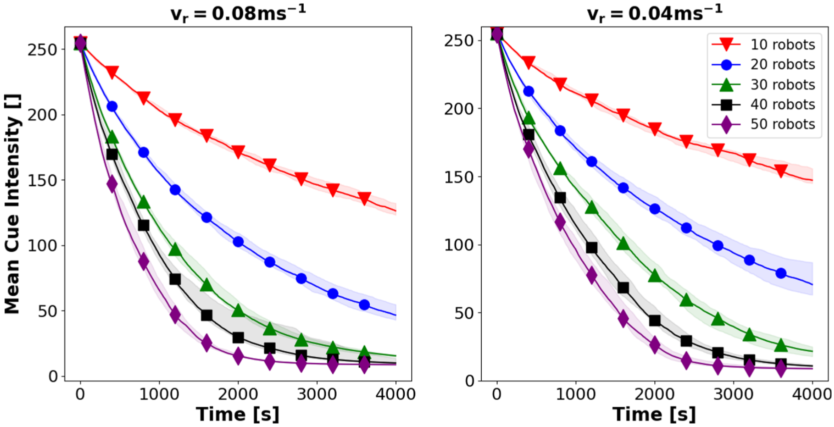


Fig. 4. Mean intensity of the cue vs time for various swarm population and robot speeds. The shaded areas around the plots indicate the min and max values.

4 Results and Discussion

To provide an example of how a chemical leakage disappears, Fig. 3 shows the chemical leakage state at $t = \{0, 1000, 4000\}$ s for $N = 30$ robots with $v_r = 0.08$ ms^{-1}. At $t = 4000$ s, it could be said that cue has been disappeared. In the following paragraphs, analyses of the results of conducted experiments are provided.

Average Cue vs Time: Figure 4 demonstrates results of two experiment cases. In each case, experiments were conducted with five different populations where each population was repeated six times with different random seeds, and the median of six experiments was plotted. At first glance, it could be deduced that according to the results, robots with $v_r = 0.08$ ms^{-1} could decrease the intensity of chemical leakage faster in comparison with robots that move by the velocity of $v_r = 0.04$ ms^{-1}. It is also apparent that as the number of robots increases, so does the vanishing speed of chemical leakage. Therefore, similar to the results of aggregation experiments in [3], the growth of the population significantly improved swarm performance. It can be seen from Fig. 4 that the best performance among test cases belongs to $N = 50$ robots with $v_r = 0.08$ ms^{-1} where the weakest performance belongs to $N = 10$ robots with $v_r = 0.04$ ms^{-1}.

The results were also statistically analyzed to find the most effective factor. Table 2 shows the results of the ANOVA test, that reveal all parameters (time, population size, and speed of robot) significantly affect the system ($p \leq 0.05$), however, speed of robot was the most significant factor ($F = 67.144$). On the other hand, the least effective factor was the time ($F = 5.032$) that shows the cleaning process is less time-dependent.

Table 2. Results of ANOVA test for the cue intensity

Factors	p-value	F-value
Time	0.000	5.032
Population	0.000	39.838
Speed	0.000	67.144

Ratio of Robots at the Source of Leakage: The ratio of robots that are close to source of leakage with a distance of less than 0.7 m for $N = \{10, 30, 40\}$ robots and $v_r = 0.08\ \mathrm{ms}^{-1}$ to all robots of that experiment case were plotted in Fig. 5(a). This ratio decreases during time and remains constant at about $t = 1500$ s for $N = \{30, 50\}$ robots. For $N = 10$ robots, it can be observed that the ratio of robots close to the center of cue does not change considerably. If $t = 1500$ s (the time that ratio remains unchanged) is observed in Fig. 4 for $N = \{30, 50\}$ robots and $v_r = 0.08\ \mathrm{ms}^{-1}$, it can be understood that for both population the intensity of cue has been reduced more than 50% by that time. So as proposed, there is an obvious connection between this metric and the previous one. When cue almost disappears, robots do not aggregate close to the center anymore and move to places with higher intensity of cue.

As proposed in metrics section, the cleaning pattern of robots can be determined from Fig. 5(a) since it can be seen that the ratio of robots which are close to the center of the cue (with a distance less than $r_c = 0.7$ m) increases significantly while the cue has not been decreased by 50%. After the noticeable increase in the ratio of robots close to the cue center, it decreases to reach its steady-state. From this manner of the ratio of robots close to the cue center, it can be concluded that at first thousand seconds, most of the robots are within the radius of $r_c = 0.7$ m, and they distribute from the center as the leakage vanishes. Therefore, robots clean the cue from inside, starting with the highest leakage points and continuing to spots with less leakage. When the cue almost disappears, they do their random walk, and at that moment, measurements in all presented plots remain steady.

In terms of studying the impact of the population size on the ratio of robots close to the cue center, it can be observed that as the population increases, the steady-state ratio decreases since the center of cue vanished more and robots tend to spread all over the environment randomly. However, the steady-state ratio will be higher for smaller populations since there are still some visible parts of the cue. Besides comparing the steady-state ratio, the slope of plots before remaining unchanged also heavily depends on the population. That way, the higher population will have sharper decreases before their steady-state since they will clean the cue quicker and more.

Coherency: Figure 5(b) demonstrates the coherency of three population sizes of $N = \{10, 30, 50\}$ robots with $v_r = 0.08\ \mathrm{ms}^{-1}$. The similar point of test cases is that they verge to a steady-state after a while. On the other hand, they differ in the slope of verging to this steady value as for higher population sizes, coherency

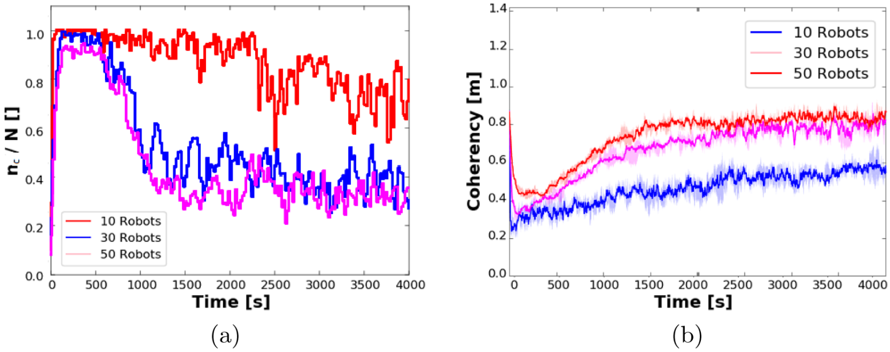


Fig. 5. (a) Ratio of robots within a distance of r_c =0.7 m from the source of leakage for $N = \{10, 30, 50\}$ robots with speed of v_r = 8.0 cm s^{-1}, and (b) Median coherency measured in meters vs time for $N = \{10, 30, 50\}$ robots with v_r = 8.0 cm s^{-1}. Shades area indicates the maximum and minimum coherency.

Table 3. Results of ANOVA test for the coherency

Factors	p-value	F-value
Time	0.000	5.214
Population	0.000	19.088
Speed	0.000	5.305

reaches its steady-state faster. To define a steady-state for coherency, we shall consider $N = 50$ robots and compare its results with previous metrics. In Fig. 4, it can seen that for $N = 50$ robots with v_r = 0.08 ms^{-1} speed, after t = 2500 s the average cue intensity does not change considerably. If the same moment is considered in Fig. 5(b), it can be seen that at that moment, coherency also does not change considerably. Therefore it can be deduced that whenever chemical leakage vanishes, coherency and average cue reach their steady-state.

There are similar features between Fig. 5(a) and Fig. 5(b). Primarily, in both figures for $N = 10$ robots, plots do not change considerably, and as the population grows, plots in both figures fluctuate more. For $N = \{30, 50\}$ robots, plots in both figures remain unchanged after t = 1500 s. To analyze this behavior, when coherency remains unchanged, there is no longer cooperation among robots. At that moment, the ratio of robots close to the center of the cue also remains constant, so the robots are not following cue anymore. Hence, they mainly tend to perform random walk. Consequently, from these observations, it can be concluded that the more the cue disappears, the tendency of robots for random walk increases, and their cooperation decreases.

In terms of comparing the effect of population size on coherency, it can be seen that as the population grows, the robots' coherency changes more dramatically. It can be observed that for $N = 10$ robots, coherency does not alter noticeably.

In contrast, for $N = 50$ robots, coherency encounters a notable decrease meaning that the robots get very close to each other while the cue is not cleaned.

The results in this section were also statistically analyzed (Table 3). The results showed that all the factors significantly affected the coherency of the swarm system ($p \leq 0.05$). However, the population was the most significant factor ($F = 19.088$) in the coherency of the robot's motion.

Although the primary goal of this work was to demonstrate an application of swarm robotics in an extreme environment, such a system will also be useful in other applications e.g., agri-robotics [11], industrial machinery [9] and outdoor localization [16].

5 Conclusion and Future Work

In this paper, a chemical leakage localization and cleanup scenario was implemented using the simulated swarm of robots. The proposed method is based on a bio-inspired aggregation scenario for swarm robots. Impacts of population and speed on swarm performance were studied. The evolution of cooperation between robots and the ratio of robots present near the source of the leakage is also studied to track the robots' interaction during the process. As the results revealed, robot cooperation decreases as leakage vanishes. Therefore, these results can be a significant guide for developing the real-world application of swarm robotics in an extreme environment.

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