DORA: Distributed Online Risk-Aware Explorer

David Vielfaure*, Samuel Arseneault*, Pierre-Yves Lajoie, Giovanni Beltrame

Abstract— Exploration of unknown environments is an important challenge in the field of robotics. While a single robot can achieve this task alone, evidence suggests it could be accomplished more efficiently by groups of robots, with advantages in terms of terrain coverage as well as robustness to failures. Exploration can be guided through belief maps, which provide probabilistic information about which part of the terrain is interesting to explore (either based on risk management or reward). This process can be centrally coordinated by building a collective belief map on a common server. However, relying on a central processing station creates a communication bottleneck and single point of failure for the system. In this paper, we present Distributed Online Risk-Aware (DORA) Explorer, an exploration system that leverages decentralized information sharing to update a common risk belief map. DORA Explorer allows a group of robots to explore an unknown environment discretized as a 2D grid with obstacles, with high coverage while minimizing exposure to risk, effectively reducing robot failures.

Index Terms— Swarm Robotics, Path Planning for Multiple Mobile Robots or Agents, Robot Safety

I. INTRODUCTION

The exploration of unknown environments is at the core of numerous robotic applications from search-and-rescue operations [1] to space missions [2]. The problem has been mostly studied in single robot setups, but the ability to perform exploration with teams of robots opens the door to even more ambitious applications, because with proper coordination, the time required to explore a given environment should decrease proportionally to the number of robots [3]. Therefore, multi-robot exploration is an attractive solution to many time-critical applications such as search-and-rescue operations or planetary exploration. Moreover, multi-robot teams are usually resilient to some amount of robot failures [4], [5], [6]. However, robot failures are still undesirable as they can affect team performance and should therefore be avoided, which is the main motivation for this work, in which we present a risk-aware exploration algorithm for multi-robot systems: Distributed Online Risk-Aware (DORA) Explorer.

Multi-robot systems come with their own sets of constraints and challenges: among those, coordination and communication are the most relevant to the exploration problem. Without coordination, the robots will inevitably explore overlapping parts of the environment, leading to little gains in terms of efficiency compared to single-robot solutions. While the coordination could be optimally orchestrated from a central computing station, such a solution would require a perfect connectivity maintenance with each robot and a high communication bandwidth since the robots would need to send their observations and receive their commands. This motivates the need for a decentralized exploration algorithm relying only on local computation onboard the robots and communication with their neighbours.

To the best of our knowledge, there exists no risk-aware collaborative exploration algorithm that relies solely on local or shared information. Therefore, in this paper, we make the following contribution to the field of multi-robot exploration: A decentralized exploration algorithm leveraging distributed belief maps (DBMs) to maximize coverage and decrease robot failure probability using risk-awareness. To evaluate this system, we test it on the specific problem of hazard mapping in a 2D world discretized as a grid, in which a multi-robot team simultaneously explores a dangerous environment and collaborates to avoid hazardous locations as well as obstacles. We first validate our approach in a physics-based simulator, ARGoS [7], in which we define a grid-based environment with multiple radiation sources and we then test it on physical robots. In our experiments, the belief of each cell models the likelihood of robot failure at that point in space due to ionizing radiation. It is worth noting that the risk of failure could originate from any other danger type, such as fire, rough terrain, etc.

II. RELATED WORK AND BACKGROUND

Distributed information sharing is not trivial, especially considering the challenges of consistency and partial connectivity among the robotic teams [8]. The virtual stigmergy presented in [9] and implemented in the Buzz programming language [10] achieves consensus among a group of robots using conflict-free replicated data types (CRDTs), represented as key-value pairs. This sort of shared data structure is particularly relevant for belief maps, since it is easy to assign a unique key to each cell based on its location. In the virtual stigmergy, data is shared on writing and reading the CRDT, with the additional updates on read improving the robustness to temporary disconnections and message drops. This solution differs from distributed hash tables, which require a complete view of the system at every point in time. Other distributed data storage approaches such as SwarmMesh [11] store data in different locations based on a fitness function instead of replicating them on all robots. This allows the storage of more data with less communication, but robots are less likely to have access to the latest values.

Belief maps are a simple yet powerful tool for robotic exploration because they can represent an environment with a 2D cell grid. They are a generalization of occupancy maps: instead of storing only one bit per cell to indicate the presence of an obstacle/danger, they store obstacle/danger likelihoods and offer significant improvements for exploration [12]. In the field of multi-robot exploration, early
techniques leveraging belief maps date back as far as twenty years [13], [14], but they rely on a fixed grid size and are tested only with two robots. More recent works also leverage belief maps for multi-robot exploration. For example, in [15], the robots consider both the current beliefs and the expected beliefs from future observations to coordinate their exploration. Grid maps and belief maps are also widely used to train deep reinforcement learning exploration policies [16], [17]. Such techniques generally achieve the best performance in simulated environments, but are usually brittle in more realistic and noisy scenarios.

Several path planners based on Markov Decision Processes [18], [19], [20] take into account risk and have useful definitions of it. However, they assume a knowledge of the global state of the environment, which is unavailable when exploring unknown environments. Furthermore, they are so far only applied to single-robot systems.

Many distributed exploration strategies that maximize the amount of covered terrain have been proposed. The first approaches to stand out in this regard are Voronoi-based coverage control techniques [21], [22]. A second method covers time-varying domains, in which points of interest in the covered region can become more or less interesting to explore, therefore prompting a change in the coverage function [22], [23]. Another method to optimize coverage is Frontier-Based Exploration (FBE) [24] of which many variations have been developed, such as those based on Particle Swarm Optimization [25] or the Wavefront Frontier Detector [26]. However, none of these strategies take risk into account, which is inherent to exploration. Therefore, the exploration strategy implemented in this paper takes inspiration of the multi-robot control algorithm presented in [27], [28] which maximizes the information gain during exploration in the presence of unknown hazards. However, this optimal algorithm has a very high computational complexity. In DORA-Explorer, we introduce approximations to lower the computation load onboard the robots which makes it well suited for real deployment on resource constrained robotic platforms.

We build on those approaches and address some their shortcomings by implementing a risk-aware exploration algorithm leveraging a DBM of the environment which is not constrained to a fixed size.

III. SYSTEM MODEL

The DORA Explorer leverages risk awareness to provide better efficiency when exploring hazardous environments. Reducing the likelihood of robot failures is of high importance as failures lead to poor exploration performance. Indeed, if robots experiencing complete failures are not replaced, individual failures lead to lower numbers of robots carrying the exploration task. As a result, fewer cells are explored at every time step and globally the rate of exploration decreases. Avoiding dangerous areas, sometimes at the cost of not exploring them, can be advantageous to the robot team as a whole, as shown in Fig. 1. By keeping robots operational, our risk-aware exploration algorithm enables the exploration of the environment with the contribution of all the team members. The workforce does not decrease and as a result, the performance of the team remains high. We model the 2D environment as cells forming a grid represented as $E \subset \mathbb{Z}^2$. The team of robots is denoted as the collection of agents $a_i \in A$.

A. Risk Modelling

Without loss of generality, we model risk considering point radiation sources, denoted by the set $S$. The intensity of each radiation source is given by $I_j \sim U(0, 1)$. Each source’s position is denoted by $s_j \in E$. Given a robot $a_i$’s discrete position $x_i \in E$, the perceived radiation level by that robot from $s_j$ is given by:

$$r_{s_j}(x_i) = \frac{I_j}{1 + \lambda \rho^2}$$  \hspace{1cm} (1)

which decays as the distance $\rho$ between $s_j$ and $x_i$ increases, and $\lambda$ is a decay constant. Measurement noise is accounted for in the form of a Gaussian background radiation $b \sim \mathcal{N}(0, 0.05)$. The total radiation perceived by a robot is:

$$r(x_i) = b + \sum_{s_j \in S} r_{s_j}(x_i)$$  \hspace{1cm} (2)

Robots are only able to sense the radiation level associated with their current position using an onboard sensor. They do not hold any knowledge of where the radiations sources are located in the environment. For the following definitions, it should be noted that $r_{s_j} : E \rightarrow [0, 1]$ and $r : E \rightarrow [0, 1]$. Let the event of robot $a_i$ failing be $f_i = 1$, the probability of such a failure due to an individual source of radiation follows a Bernoulli distribution: $\mathbb{P}(f_i = 1|s_j) \sim B(r_{s_j}(x_i))$. We assume that the sources of radiation affect the robots independently, so the probability of a robot failing due to the combined effect of all radiation sources is given by:

$$\mathbb{P}(f_i = 1|S) = \prod_{s_j \in S} \mathbb{P}(f_i = 1|s_j)$$  \hspace{1cm} (3)

which also follows a Bernoulli distribution such that $\mathbb{P}(f_i = 1|S) \sim B(r(x_i))$.

B. Information Modelling

The objective of exploring an unknown dynamic environment is to gain information about it. Moreover, this information should be as up to date as possible. Therefore, it is unlikely that visiting a recently explored cell will yield any significant gain as the information should not have changed drastically. Conversely, exploring areas visited long ago should yield a greater information gain, and unvisited areas should provide the highest information gain. The last time of exploration $t_e$ by robot $a_i$ of a cell at position $x_i$ can be represented by the scalar field $\epsilon(x_i) = t_e$. Let $u_i = 1$ be the event of robot $a_i$ finding useful information in a cell and $\Delta t = t - t_e$ the time elapsed since the cell was last visited, with $t$ being the current time. Then, the probability of not finding useful information $\mathbb{P}(u_i = 0|f_i = 0, \Delta t)$ can
be modelled as an exponential distribution with the following probability density function:

$$f(\Delta t; \omega) = \begin{cases} \omega e^{-\omega \Delta t}, & \text{if } \Delta t \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

where $\omega$ is the rate parameter of the distribution. In words, the longer the cell has not been visited, the higher the chance something has changed and consequently the lower the chance of not finding useful information. It follows that the probability of finding useful information is:

$$P(u_i = 1|f_i = 0, \Delta t) = 1 - P(u_i = 0|f_i = 0, \Delta t)$$

Intuitively, no information can be acquired by failed robots, which can be expressed as:

$$P(u_i = 1|f_i = 1) = 0$$

C. Distributed Belief Map

As previously stated, we implement a DBM using the virtual stigmergy [9] from the Buzz [10] programming language. Because $r(x_i)$ and $\epsilon(x_i)$ are both scalar fields, they lend themselves particularly well to being stored in a CRDT at a low cost. At each time step, the robots store their values of $r(x_i)$ and $\epsilon(x_i)$ in their respective stigmergies. The inputs to both fields can be used as keys (more precisely, a concatenation of $x_{i:x}$ and $x_{i:y}$). This means that the cost of storing the information for a given time step is very low, especially as the keys consist of a few characters and the values are floating point numbers. Storing the information into the DBM via the virtual stigmergy allows robots to share their observations as it is accessible by every robot in the system. Thus, a robot visiting a cell for the first could still have information from which to compute a good control policy if this cell was previously visited by another robot. In the event of a collision in the stigmergy (when robots write to the same key in the same $t$) the data from the highest robot ID is kept. When a robot writes to a key already present in the stigmergy (from a previous time step), the new data is merged with an average. The stigmergies do not directly store probabilities and thus cannot be strictly considered as belief maps [13]. However, $r(x_i)$ and $\epsilon(x_i)$ vary monotonically in the same directions as $P(f_i = 1|S)$ and $P(u_i = 1|f_i = 0, \Delta t)$ respectively, so they can be used to formulate a control law based on the optimization of these probability functions.

D. Control Law

We assume that robots can be controlled through a position-based control law. The best control policy should attempt to minimize probability of failure and to maximize the information gain. While the directions achieving these individual objectives might be at odds in the short term, they are in fact complementary in the long term because no information can be gained if a robot failed, as defined by (6), which means that avoiding danger implicitly leads to more opportunities of gaining information [28].

For a robot at a given position $x_i$, the directions where the risk is minimized and the information gain is maximized are respectively $\nabla r(x_i)$ and $\nabla \epsilon(x_i)$, also denoted as $\nabla r_{i:i}$ and $\nabla \epsilon_{i:i}$. Calculating these globally at every time step is too computationally expensive [27], [28]. Instead, we compute them locally in a Moore neighborhood $\nu$ centered on $x_i$ as shown in Fig. 2 where each neighboring cell $n_{i,j} \in \nu$ is a vector in $\mathbb{Z}^2$ representing an offset from $x_i$. We then have:

$$\frac{\partial r}{\partial n_{i,j}} = r(x_i) - r(n_{i,j})$$

$$\nabla r_{i:j} = \sum_{n_{i,j} \in \nu} \frac{\partial r}{\partial n_{i,j}} \hat{n}_{i,j}$$

where $\hat{n}$ is the unit form of $n$. The exploration gradient $\nabla \epsilon_{i:j}$ is calculated similarly. The movement vector $m_i \in \mathbb{R}^2$ for the next time step gives a good enough approximation for short term trajectory planning while relying only on local information and is given by:
\begin{equation}
\mathbf{m}_i = \alpha \nabla_{r_i} + \beta \nabla_{e_i} + \gamma \mathbf{a}_i \tag{9}
\end{equation}

where $\alpha, \beta, \gamma$ are respectively the risk avoidance, exploration and obstacle avoidance control gains. The parameters can be adjusted arbitrarily, setting them to zero will remove the effect of the corresponding control law. The obstacle avoidance vector was included to ensure robustness and is taken from [29]. With $\tilde{m}_i$ being the normalized vector movement and $k$ a speed constant, the control law for an agent $a_i$ at time step $t$ is expressed as:

\begin{equation}
x_{i}^{t+1} = x_{i}^{t} + k\tilde{m}_{i}^{t} \tag{10}
\end{equation}

E. Implementation

The DBMs and the control law previously described are combined in Alg. 1 to describe the behavior of an agent. At every time step, the information from the DBMs is used to determine the agent's next movement. The DBMs are then updated with the new information gained. Global exploration efficiency emerges through the exchange of information through the stigmergies, but no explicit coordination is required otherwise. Unlike FBE algorithms, DORA never stops exploring the environment even if all cells are covered, as information could be gained by visiting "old" cells. If $||\tilde{m}_i||$ is too small, the agents move forward to avoid stagnation.

\begin{algorithm}
\caption{DORA Execution Loop}
\begin{algorithmic}
\State $x \leftarrow \text{random\_coordinates}$
\While{$\text{True}$} 
\State $\nabla_{r_i}, \nabla_{e_i} \leftarrow (0,0), (0,0)$
\For{$n \in \nu$} 
\State $\nabla_{r} \leftarrow \nabla_{r} + (r_{\text{stig}}[x] - r_{\text{stig}}[n]) \cdot \text{normalize}(n)$
\State $\nabla_{e} \leftarrow \nabla_{e} + (e_{\text{stig}}[x] - e_{\text{stig}}[n]) \cdot \text{normalize}(n)$
\EndFor
\State $\mathbf{m} \leftarrow \alpha \nabla_{r_i} + \beta \nabla_{e_i} + \gamma \cdot \text{compute\_avoidance}(\text{sensors})$
\State $x \leftarrow x + k \cdot \text{normalize}(\mathbf{m})$
\State $r_{\text{stig}}[x], e_{\text{stig}}[x] \leftarrow \text{get\_radiation}(), \text{time}()$
\EndWhile
\end{algorithmic}
\end{algorithm}

F. Scalability

To achieve scalability to a high number of agents and to large environments, DORA Explorer must have both low communication costs and low computational costs. Lowering the communication costs associated with sharing the belief map can be done by using the virtual stigmergy, which is designed to limit information exchange to read or write operations only on the requested data. Because DORA relies solely on local information, the data transfer cost $D(A, \nu, E)$ for an agent at a given time step is independent from the total number of agents in $A$ and from the size of the environment $E$. For a neighboring cell $n_{i,j} \in \nu$, 2 stigmergy read operations are needed per time step: one each to read $r(n_{i,j})$ and $\epsilon(n_{i,j})$. In the same time step, the agent updates $r(x_i)$ and $\epsilon(x_i)$ after it has moved to a new location, which requires 2 stigmergy write operations. Each stigmergy access requires only a few tens of bytes of data transfer for the key and value. This mostly constant data quantity is represented as $d$, we have $D(A, \nu, E) = 2d(\nu| + 1)$. Similarly, the computational cost $C(A, \nu, E)$ for the same agent at the same time step is kept very low because of the reliance on local information only. Each time step requires to compute 2 gradients, and referring to (7), (8), (9) and (10) we have that $C(A, \nu, E) = 12|\nu| + 7$. The costs related to $\mathbf{a}_i$ have been excluded from this analysis as obstacle avoidance is not a critical part of DORA. The communication and computational costs for an agent at very time step are therefore both bounded by:

\begin{equation}
D(A, \nu, E) \text{ and } C(A, \nu, E) \in \Theta(|\nu|) \tag{11}
\end{equation}

Such low costs mean that DORA should scale well to a large number of robots and should enable real time computation for even the simplest robots.

IV. SIMULATIONS

A. Experimental setup

We tested our system through simulations in ARGoS [7], which is an open-source physics-based simulation environment designed for robotic swarms. The agents we used in the simulation are KheperaIV robots [30]. These are small round robots (140mm of diameter) equipped with 8 infrared proximity sensors spread evenly around their frame to perform obstacle avoidance. The agents behavior is implemented using Buzz to facilitate swarm management and interaction.

[Fig. 3: 400m$^2$ environment in the ARGoS simulator with 20 KheperaIV robots. Cylinders are radiation sources and boxes are random obstacles.]

We deployed a set of $N = \{10, 15, 20\}$ robots in a simulated environment of 20m by 20m with set of 2 radiation sources. The robots’ initial positions are chosen randomly. We set $\lambda$ from (1) to be 5 and $k$ from (10) to be 20. Because no information gain can be achieved by a failed robot as seen in (6), failure must be avoided. This leads to choosing $\alpha \geq \beta$ in (10). For our experiments, we set $\alpha = 2, \beta = 1$ and $\gamma = 1$. The robots are all given a random initial orientation. Radiation sensing is emulate by an ARGoS controller reading the randomly generated radiation sources. Failures are randomly triggered by using (3): if $f_i = 1$, the robot stops exploring. We added 5 randomly distributed 0.8m
performs both FBE and the random walk, as it is its main
in line with the benefits associated with swarm algorithms.

The following figures show an average of the results
obtained in the 50 simulation runs of each algorithm.

At the beginning of the exploration process, DORA and
the baselines perform similarly in terms of number of cells
explored as shown in Fig. 5a, 5b, and 5c. As time progresses
in the same figures, FBE achieves a slightly higher explo-
ration coverage than DORA, but this gap in performance
decreases as the number of robots increases. This is an
expected result, because DORA’s main goal is not to achieve
maximal coverage at all costs, unlike FBE. Both FBE and
DORA clearly outperform the random walk algorithm. The
other trend is that adding more robots to the swarm results
in faster exploration, with a higher number of cells being
explored for all three algorithms after 300 steps. This shows
that DORA scales well to large number of robots, and even
gains in performance when swarm size increases, which is
in line with the benefits associated with swarm algorithms.

In terms of avoiding failures, DORA unsurprisingly out-
performs both FBE and the random walk, as it is its main
purpose. This is shown in Fig. 6a, 6b, and 6c where DORA
exhibits a higher level of active robots over time, with this
difference only increasing with larger swarm sizes. For N =
\{10, 15, 20\} robots, there are rarely any survivors for FBE,
and random walks perform only slightly better. In contrast,
DORA keeps most robots alive, achieving its objective.

The results from Fig. 4 show the amount of data trans-
ferred by individual agents at each time step by both al-
gorithms. We excluded the random walk algorithm from
this figure as it does not require any coordination or com-
munication between its agents. DORA transmits more data
than FBE, which was expected because the former shares
information through two DBMs, while the latter uses only
one. In section III-F we predicted that the amount of data
transmitted at each time step would only depend on the size
of the neighborhood used, and this is confirmed by Fig. 4
where it remains roughly constant for different number of
agents. The small increase in data transmission with increas-
ing number of robots can be attributed to packet collision.
Overall, the amount of required data transfer is small in
comparison with the capacities of the KheperaIV robots
which communicate with the 802.11 b/g WiFi protocol.

Fig. 7 shows the DBMs obtained at the end of an arbi-
trarily selected simulation where N = 20 for each algorithm.
In other words, it represents which cells were explored by
each algorithm and the sensed radiation intensity associated
with them for one specific run. The random walk covered
much fewer cells than DORA and FBE, which both covered
roughly the same areas of the map, with the same sections
remaining unexplored. However, these areas remained un-
visited for different reasons. For FBE, the parts of the envi-
riment close to the radiation sources remained uncovered
because its agents failed when approaching them. In contrast,
DORA did not explore these cells because it avoided them.
Again, DORA achieves very similar coverage than FBE but
does so with less robot failures. In this particular simulation,
DORA finished with 18 active robots, random walk finished
with 7, and FBE with none.
V. PHYSICAL EXPERIMENTS

A. Experimental setup

In addition to the extensive simulations conducted in ARGoS, we tested our system on a team of three physical KheperaIV robots in a 2m x 2m environment containing 1 point radiation source as shown in Fig. 8. We only used one radiation source because of the small size of the environment.

The environment is discretized as a 10 x 10 grid, meaning that each of the 100 cells of the grid is 20cm x 20cm large. Because the arena in which we conducted the experiments was already limited in terms of space we decided not to add obstacles. Positioning of the robots is done using an OptiTrack motion capture system. For outdoor applications where the environment is bigger, positioning of the robots could instead be achieved by GPS. Radiation sensing is emulated by an on board controller that reads the distance between the robot and the radiation source to determine the current radiation level. Failures are then triggered using equation (3), in other words the higher the radiation level,
the higher the probability of failure. If a robot fails, it stops moving and as a result stops contributing to the exploration effort. The point radiation source is located in a corner of the arena and the robots are initially placed in the three remaining corners. The robots’ initial orientations are chosen randomly. We performed 5 runs over 200 steps of the DORA exploration algorithm. Again, to assess DORA’s performance, we compare it to the results obtained by FBE and random walk algorithms.

B. Results

Figs. 9 and 10 show an average of the results obtained in the 5 runs of each algorithm on physical robots.

![Fig. 9: Performance comparison of DORA, FBE and random walk for number of explored cells over time on physical robots.](image)

![Fig. 10: Performance comparison of DORA, FBE and random walk for number of active robots over time on physical robots.](image)

At the beginning of the exploration process, DORA and FBE perform similarly in terms of number of cells explored as shown in Fig. 9. The random walk algorithm’s exploration rate is considerably smaller which can be attributed to the fact that some of the cells of the environment are visited multiple times; robots sometimes come back to positions that they just had visited since their motion is determined randomly. As time progresses, DORA starts showing better exploration results than FBE and at the end of the runs DORA achieves a considerably better coverage. Both FBE and DORA clearly outperform the random walk algorithm.

In terms of robot failures, DORA outperforms both FBE and the random walk algorithm. This is shown in Fig. 10, where DORA exhibits a higher level of active robots over time. When using FBE, all three robots always fail before the end of the 200 steps run. Random walk shows a level of active robots that is in between DORA and FBE.

The results show that while DORA and FBE initially have similar performances, as time progresses, DORA gets better when compared to FBE. This is directly linked to the robot failures occurring in the system. Indeed, because FBE experiences a lot of failures, the failed robots stop exploring and, as a result, the exploration rate decreases dramatically. In fact, FBE always loses all its robots before the end of the experiments, hence the robotic team completely stops discovering new cells. In contrast, DORA keeps most of its robots active throughout the experiment and since the workforce does not decrease to exploration rate remains high.

VI. Conclusion

We presented DORA Explorer, a novel lightweight risk-aware exploration algorithm that minimizes the risk to which robots expose themselves in order to maximize the amount of ground they will be able to cover without failing. We expected that our exploration algorithm, which leverages DBMs, would greatly outperform non-coordinated solutions, and this has been the case. Indeed, it succeeded in reducing considerably the likeliness of robot failures while keeping similar ground coverage performance compared to other solutions proposed in the literature. DORA also showed good scalability thanks to its low communication costs. It also showed applicability to real world scenarios through experiments with physical robots.

In future work, it could be interesting to allow DORA to become more or less risk-avoiding depending on the changing needs of the situation. For example, in a search-and-rescue scenario, an increasing urgency to rescue victims could motivate the willingness to take more risks as time progresses. Also, more experiments could be conducted by testing DORA Explorer on a larger team of physical robots exploring larger outdoor environments. Further applications of DORA could include using the generated risk belief map to determine robots’ fitness to store data in distributed storage systems like SwarmMesh [11], with robots assigned to tasks in dangerous regions being discouraged from storing sensitive information. Additionally, in this work we considered that the risk associated with the environment can be sensed by the robots. However, in some scenarios, the risk cannot be directly perceived by any sensors. In these cases, the belief map could be constructed using the previous failures of the agents by assigning risk to areas where failures have been detected in the past.

REFERENCES

[1] A. Matos, A. Martins, A. Dias, B. Ferreira, J. M. Almeida, H. Ferreira, G. Amaral, A. Figueiredo, R. Almeida, and F. Silva, “Multiple robot operations for maritime search and rescue in
eulathon 2015 competition,” in OCEANS 2016-Shanghai. IEEE, 2016, pp. 1–7. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7485707

[2] T. Fong and I. Nourbakhsh, “Interaction challenges in human-robot space exploration,” *Interactions*, vol. 12, no. 2, pp. 42–45, 2005. [Online]. Available: https://dl.acm.org/doi/10.1145/1052438.1052462

[3] W. Burgard, M. Moors, C. Stachniss, and F. E. Schneider, “Coordinated multi-robot exploration,” *IEEE Transactions on Robotics*, vol. 21, no. 3, pp. 376–386, 2005. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/1435481

[4] R. K. Ramachandran, J. A. Preiss, and G. S. Sukhatme, “Resilience by reconfiguration: Exploiting heterogeneity in robot teams,” *arXiv preprint arXiv:1903.04856* (2019). [Online]. Available: https://arxiv.org/abs/1903.04856

[5] R. Wehbe and R. K. Williams, “Probabilistic resilience of dynamic multi-robot systems,” *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 1777–1784, 2021. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9375930

[6] A. F. Winfield and J. Nembrini, “Safety in numbers: fault-tolerance in robot swarms,” *International Journal of Modelling, Identification and Control*, vol. 1, no. 1, pp. 30–37, 2006. [Online]. Available: https://www.inderscienceonline.com/doi/abs/10.1504/IJMIGC.2006.008645

[7] C. Pinciroli, V. Trianni, R. O’Grady, G. Pini, A. Brutschy, M. Brambilla, N. Mathews, E. Ferrante, G. Di Caro, F. Ducatelle, M. Birattari, L. M. Gambardella, and M. Dorigo, “ARGoS: a modular, parallel, multi-robot simulator for multi-robot systems,” *Swarm Intelligence*, vol. 6, no. 4, pp. 271–295, 2012.

[8] F. Amigoni, J. Banfi, and N. Basilico, “Multirobot exploration of communication-restricted environments: A survey,” *IEEE Intelligent Systems*, vol. 32, no. 6, pp. 48–57, 2017. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8267592

[9] C. Pinciroli, A. Lee-Brown, and G. Beltrame, “A tuple space for data sharing in robot swarms,” in Proceedings of the 9th EAI International Conference on Bio-inspired Information and Communications Technologies (formerly BIOTECNET), 2016, pp. 287–294. [Online]. Available: https://arlo.pinciroli.net/pdl/Pinciroli:BICT2015.pdf

[10] C. Pinciroli and G. Beltrame, “Bzzz: A programming language for robot swarms,” *IEEE Software*, vol. 33, no. 4, pp. 97–100, 2016.

[11] N. Majerczyk and C. Pinciroli, “Swarmmesh: A distributed data structure for cooperative multi-robot applications,” in 2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020, pp. 4059–4065. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9197403

[12] C. Stachniss and W. Burgard, “Mapping and exploration with mobile robots using coverage maps,” in Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453), vol. 1. Las Vegas, Nevada USA: IEEE, 2003, pp. 467–472.

[13] F. Kobayashi, S. Sakai, and F. Kojima, “Sharing of exploring information using belief measure for multi robot exploration,” in 2002 IEEE World Congress on Computational Intelligence. 2002 IEEE International Conference on Fuzzy Systems, FUZZ-IEEE’02. Proceedings (Cat. No.02CH37291), vol. 2. May 2002, pp. 1544–1549 vol.2.

[14] ——, “Determination of exploration target based on belief measure in multi-robot exploration,” in Proceedings 2003 IEEE International Symposium on Computational Intelligence in Robotics and Automation. Computational Intelligence in Robotics and Automation for the New Millennium (Cat. No.03EX694), vol. 3. Jul. 2003, pp. 1545–1550 vol.3.

[15] V. Indelman, “Cooperative multi-robot belief space planning for autonomous navigation in unknown environments,” *Autonomous Robots*, vol. 42, no. 2, pp. 353–373, Feb. 2018.

[16] L. Han, P. Sun, Y. Du, J. Xiong, Q. Wang, X. Sun, H. Liu, and T. Zhang, “Grid-wise control for multi-agent reinforcement learning in video game AI,” in Proceedings of the 36th International Conference on Machine Learning, ser. Proceedings of Machine Learning Research, K. Chaudhuri and R. Salakhutdinov, Eds., vol. 97. PMLR, 09–15 Jun 2019, pp. 2576–2585. [Online]. Available: http://proceedings.mlr.press/v97/han19a.html

[17] A. I. Panov, K. S. Yakovlev, and R. Suvorov, “Grid Path Planning with Deep Reinforcement Learning: Preliminary Results,” *Procedia Computer Science*, vol. 123, pp. 347–353, 2018.

[18] A. Undurti and J. P. How, “An online algorithm for constrained pomdp’s,” in 2010 IEEE International Conference on Robotics and Automation. IEEE, 2010, pp. 3966–3973. [Online]. Available: https://doi.org/10.1109/ROBOT.2010.5509743

[19] S. Thiebaux, B. Williams et al., “Rao*: An algorithm for chance-constrained pomdp’s,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 30, no. 1, 2016. [Online]. Available: https://ojs.aaai.org/index.php/AAAI/article/view/10423

[20] X. Xiao, J. Dutké, and R. R. Murphy, “Robot risk-awareness by formal risk reasoning and planning,” *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2856–2863, 2020. [Online]. Available: https://doi.org/10.1109/LRA.2020.2974434

[21] W. Luo and K. Sycara, “Voronoi-based coverage control with connectivity maintenance for robotic sensor networks,” in 2019 International Symposium on Multi-Robot and Multi-Agent Systems (MRS). IEEE, 2019, pp. 148–154. [Online]. Available: https://ieeexplore.ieee.org/document/8901078

[22] M. Santos, S. Mayya, G. Notomista, and M. Egerstedt, “Decentralized minimum-energy coverage control for time-varying density functions,” in 2019 International Symposium on Multi-Robot and Multi-Agent Systems (MRS). IEEE, 2019, pp. 179–181. [Online]. Available: https://ieeexplore.ieee.org/document/8901067

[23] X. Xu and Y. Díaz-Mercado, “Multi-robot control using coverage over time-varying domains,” in 2019 International Symposium on Multi-Robot and Multi-Agent Systems (MRS). IEEE, 2019, pp. 179–181. [Online]. Available: https://ieeexplore.ieee.org/document/8901067

[24] B. Yamauchi, “Frontier-based exploration using multiple robots,” in *Proceedings of the second international conference on Autonomous agents*, 1998, pp. 47–53. [Online]. Available: https://dl.acm.org/doi/10.1145/280765.280773

[25] Y. Wang, A. Liang, and H. Guan, “Frontier-based multi-robot map exploration using particle swarm optimization,” in 2011 IEEE symposium on Swarm intelligence. IEEE, 2011, pp. 1–6. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/5952584

[26] A. Topiwala, P. Inani, and A. Kathpal, “Frontier based exploration for autonomous robot,” *arXiv preprint arXiv:1806.03581* (2018). [Online]. Available: https://arxiv.org/abs/1806.03581

[27] P. Dames, M. Schwager, V. Kumar, and D. Rus, “A decentralized control policy for adaptive information gathering in hazardous environments,” in 2012 IEEE 51st IEEE Conference on Decision and Control (CDC). IEEE, 2012, pp. 2807–2813. [Online]. Available: https://ieeexplore.ieee.org/document/6426239

[28] M. Schwager, P. Dames, D. Rus, and V. Kumar, “A Multi-robot Control Policy for Information Gathering in the Presence of Unknown Hazards,” in Robotics Research : The 15th International Symposium ISRR, ser. Springer Tracts in Advanced Robotics, H. I. Christensen and O. Khatib, Eds. Cham: Springer International Publishing, 2017, pp. 455–472.

[29] M. Shahriari, I. Švogor, D. St-Onge, and G. Beltrame, “Lightweight collision avoidance for resource-constrained robots,” in 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2018, pp. 1–9. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8593841

[30] K-Team, “Khepera IV,” 2021. [Online]. Available: https://www.k-team.com/khepera-iv