Self-Healing Ground-and-Air Connectivity Chains

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Abstract—The coordination of robot swarms – large decentralized teams of robots – generally relies on robust and efficient inter-robot communication. Maintaining communication between robots is particularly challenging in field deployments. Unstructured environments, limited computational resources, low bandwidth, and robot failures all contribute to the complexity of connectivity maintenance. In this paper we propose a novel lightweight algorithm to navigate a group of robots in complex environments while maintaining connectivity by building a chain of robots. The algorithm is robust to single robot failures and can heal broken communication links. The algorithm works in 3D environments: when a region is unreachable by wheeled robots, the chain is extended with flying robots. We test the performance of the algorithm using up to 100 robots in a physics-based simulator with three mazes and different robot failure scenarios. We then validate the algorithm with physical platforms: 7 wheeled robots and 6 flying ones, in homogeneous and heterogeneous scenarios.

I. INTRODUCTION

Swarm robotics is a field of engineering studying the use of large groups of simple robots (generally with low sensing and computation capabilities) to perform complex tasks [1]. Ideally, a single robot failure in a swarm does not compromise the overall mission because of the inherent redundancy of the swarm [2]. With robustness to individual failures and scalability, the deployment of robotic swarms is foreseen as cost effective solution for spatially distributed tasks over large areas such as exploration [3], search and rescue [4], and area coverage [5].

In many such applications, coordination among the robots is of vital importance and the ability to coordinate depends largely on the ability of the swarm to communicate. A reliable communication infrastructure allows the robots to exchange information at any time. However, in reality there are many sources of failures (environmental factors, wear and tear, etc) that can break connectivity and compromise the deployment. Consider the Fukushima accident in 2011: robots were deployed to inspect the collapsed nuclear power plant (transmitting a video feed), but were subject to extreme failures and scalability, the deployment of robotic swarms largely on the ability of the swarm to communicate. A reliable communication infrastructure allows the robots to exchange information at any time. However, in reality there are many sources of failures (environmental factors, wear and tear, etc) that can break connectivity and compromise the deployment. Consider the Fukushima accident in 2011: robots were deployed to inspect the collapsed nuclear power plant (transmitting a video feed), but were subject to extreme failure rates due to radiation.

In our previous work [6], we introduced a chain-forming algorithm in 2-dimensional uncluttered spaces. This paper extends the approach to complex tridimensional environments and heterogeneous robot teams. We propose a decentralized, failure-tolerant chain-forming algorithm that can preserve a desired network topology while navigating a complex environment and completing mission goals. Our approach is lightweight, leaving processing power for other parallel tasks.

In practice, we progressively use the available robots of a swarm to form a communication chain from a ground station to a target. We set the desired network structure by specifying the minimum number of links that should be maintained between the robots, target, and ground station. Our algorithm uses a path planner (e.g. RRT* [7]) to generate a viable path, and then uses this path as a template to build a chain of robots towards the target. The contributions of this work can be summarized as: 1) the mathematical formulation of the self-healing chain-forming algorithm, that progressively places the robots towards the target with a configurable network structure; 2) the performance evaluation with various level of injected failures in three simulated complex environments using a physics-based simulator; 3) the validation of the algorithm with a small swarm of 7 wheeled and 6 flying robots, in homogeneous and heterogeneous team deployments. This paper is organized as follows: we start with a brief summary of the related work in Section II then we detail our model in Section III and our proposed algorithm in Section IV. Finally, section V provides the experimental results.

II. RELATED WORK

The problem of preserving connectivity is widely discussed in the literature, including several recent contributions [8], [9], [10], [11]. Many of these approaches compute an algebraic connectivity metric [12]: a computationally intensive approach and sensitive to noise for distributed implementations [13]. A handful of other approaches exert virtual forces on the swarm members to preserve a pre-existing topology [14], [15], [16].

One approach is to design reactive control laws using connectivity as an imposed constraint. For example, in [17] two control laws were developed for rendezvous and formation tasks, maintaining an initially connected configuration and effectively preserving connectivity. A similar approach was implemented in [18], achieving rendezvous among a group of agents and preserving an initial connected condition using a potential based controller. The approaches that fall into this category rely on global coordination, reducing their overall scalability, i.e. making them less appropriate for larger groups of robots.

Other works are more explicitly dealing with dynamic connectivity as they implement control laws that maximize an algebraic measure of connectivity (i.e. the second eigenvalue of the Laplacian of the robots’ connectivity graph).
One notable example is [19], which describes a method for the distributed estimation of algebraic connectivity using a power iteration. The authors use this estimation to drive swarm members in such a way that maximizes algebraic connectivity. Kim et al. [20] propose a different approach that solves an optimization problem for the relative locations of robots, again to maximize the second eigenvalue of the Laplacian. Another distributed approach [21] computes the Fiedler vector (the eigenvector corresponding to the second eigenvalue of the Laplacian), and then estimates other relevant elements of the Laplacian to derive a gradient-based control law that maximizes connectivity. The main advantage of these methods is that they work fairly well for any network topology. However, the downside of using algebraic connectivity is that the distributed estimation of the adjacency matrix requires heavy usage of the communication bandwidth to converge to a reasonable value. The time required to compute the algebraic connectivity and its sensitivity to noise limits its applicability to field missions.

Another class of methods enforce the desired connectivity among robots by constructing and maintaining a given communication topology. For instance, Schuresko et al. [22] describe a robust and mission-agnostic algorithm that generates a connected spanning tree. Aragues et al. [23] implement an area coverage mission while preserving a minimum spanning tree among robots. This approach maintains connectivity with minimal interference on the area coverage mission. However, this approach requires specific initial conditions such as a fully connected network, which cannot always be guaranteed during field deployment. Majcherczyk et al. [10] treat the problem of decentralized deployment of multiple robots to different target locations while preserving connectivity. Their algorithm assigns roles for robots, such that when a target is specified, a branch of the robot network is deployed and additional robots are supplied to build a structure reaching the target while maintaining connectivity. Panerati et al. [8] proposed a hybrid methodology with a navigation controller enforcing connectivity and a global scheduler to provide the navigation controller with optimal policies. Despite the use of a global scheduler to support the navigation controller, the approach is relatively slow in comparison with ours. In addition, to the best of authors’ knowledge, none of the previous connectivity preservation approaches consider navigating a complex 3D environment with obstacles using a path planner.

Our work is comparable to [24] and [10], as we dynamically build structures to reach given targets. However, there are several differences and advantages in our approach: the ability to navigate a complex environment with obstacles, the ability to preserve a network structure with a given number of redundant links, and the support of flying robots for navigating zones deemed unreachable by ground robots. Finally, our approach minimizes the computation and communication load of each robot, allowing deployment of other behaviors on top of the connectivity maintenance algorithm.

### III. Model

#### A. Communication model

![Diagram](image)

We consider a swarm of N mobile robots capable of broadcasting messages over a limited communication range $Z$ using a range and bearing sensor [25]. This means that the receiver of a broadcast message can estimate the relative position of the sender in its local coordinate frame.

Fig. 1 shows how the surroundings of robot $i$ are divided into circular communication zones:

- the safe communication zone $Z_i^s$, in which neighbors are considered as having a reliable network link;
- the critical communication zone $Z_i^c$, in which neighbors are getting close to the limit of the communication range. In this zone, $e_c = d_c - d_s > 0$ is defined as the critical tolerance;
- the break-away zone $Z_i^b$, in which neighbors are expected to break their network link. In this zone, $e_b = d_b - d_s > 0$ is defined as the break-away tolerance.

Inter-agent communication can be modeled as an undirected graph $G = (\nu, \epsilon, A)$, with the node set $\nu = \{r_1, \ldots, r_N\}$ representing the robots, and the edge set $\epsilon = \{e_{ij}|i, j \in \nu, i \neq j\}$, representing communication links. A common approach to working with a communication graph is to use its adjacency matrix $A$, in which entries $e_{ij}$ represent the ability to communicate between two robots ($i$ and $j$). However, for most network topologies, robots do not have the complete graph and can only compute a portion of the adjacency matrix based on its local neighborhood. Let $N_i$ be the neighbor set of robot $i$, which is divided into:

$$N_i = N_i^s \cup N_i^c \cup N_i^b.$$  

Robot $j$ is called the safe zone robot of robot $i$ if $x_j \in Z_i^s$, with $x_j$ its position vector. The set of all neighbors within the safe communication zone of robot $i$ is:

$$N_i^s = \{j|x_j \in Z_i^s, \forall j \in N_i\}. \tag{1}$$

From this, we define the safe connectivity set as entries $e_{ij}$ of the adjacency matrix $\forall j \in N_i^s$. Similarly, if $x_j \in Z_i^c$, then robot $j$ is called a critical zone robot of robot $i$ and the set of critical neighbors for $i$ is:

$$N_i^c = \{j|x_j \in Z_i^c, \forall j \in N_i\}. \tag{2}$$
The associated entries $e_{ij}$ of the adjacency matrix $\forall j \in N_i$ are called the critical connectivity set. Finally, a robot $j$ with $x_j \in Z_i^b$ is called a break-away zone robot of robot $i$. The set of break-away neighbors of robot $i$ is:

$$N_i^b = \{ j | x_j \in Z_i^b, \forall j \in N_i \}.$$  (3)

The associated entries $e_{ij}$ of the adjacency matrix $\forall j \in N_i^b$ are called the break-away connectivity set.

The formulation of these sets allow us to derive control inputs for the robots that guarantee the preservation of local connectivity and to achieve a desired global network topology.

### B. Local connectivity preservation

In this section, the constraint to guarantee the preservation of connectivity among the robots are adapted from the formulation of [24].

Fig. 2. Illustration of the variables related to inter-robot distance and robots position before and after a time step $\Delta t$.

Fig. 2 shows the initial position of robot $i$ $(x_i(t))$ and robot $j$ $(x_j(t))$ with their relative distance $d_{ij}(t)$, together with their new position and relative distance after $\Delta t$. To guarantee the preservation of the communication link, the control must ensure:

$$\|\Delta x_i\| + \|\Delta x_j\| \leq d_b - d_{ij},$$  (4)

with $d_b$ a boundary distance. In our implementation we choose to split the responsibility of respecting the available margin $d_b - d_{ij}$ equally over the two robots, leading to the following theorem.

**Theorem 1**: Connectivity $e_{ij}$ between two robots $i$ and $j$ is preserved if the change in position of the robots satisfies the following condition:

$$\|\Delta x_i\| \leq \frac{d_b - d_{ij}}{2} \quad \text{and} \quad \|\Delta x_j\| \leq \frac{d_b - d_{ij}}{2},$$  (5)

**Proof**: With $d_{ij}(t+\Delta t)$ the distance between the two robots $i$ and $j$ after a time step $\Delta t$ defined as $d_{ij}(t+\Delta t) = \|x_i(t+\Delta t) - x_j(t+\Delta t)\|$, or $d_{ij}(t+\Delta t) = d_{ij}(t) + \|\Delta x_i + \Delta x_j\|$. When the condition in (5) is applied to the above equation, we get:

$$d_{ij}(t+\Delta t) \leq d_b,$$  (6)

proving that robots $i$ and $j$ stay connected. Since three neighborhood sets exist for any given robot, we discussed the applicability of the previous proof in all three cases:

1) A robot $j$ can be in $N_i^a$ if and only if, its position lies within the safe zone $Z_i^a$ of robot $i$, as given in Equ. (1)

2) For robots $j \in N_i^b$, located in the critical communication zone $Z_i^c$, if we choose control inputs that allow $\Delta x_i$ and $\Delta x_j$ to satisfy the condition of (5), with $d_s$ again as the boundary, the robots will always stay within the safe communication distance:

$$\Delta x_i \leq \frac{d_s - d_{ij}}{2} \quad \text{and} \quad \Delta x_j \leq \frac{d_s - d_{ij}}{2}$$  (7)

3) We can apply an identical reasoning for robots $j \in N_i^c$ with their position within and break-away communication zone $Z_i^b$.

### C. Global Connectivity Chains

Given a group of robots, we build a chain from a ground station to a target location. To build the chain, we assign task-related roles and relationships to the robots. Robots in the chain are assigned parent-child relationships, to manage the construction of the chain towards a target while maintaining connectivity.

**Definition 1**: A connectivity chain is a tree $T$ represented as a partially ordered set $(T, \prec) = \{ t_1, t_2, ..., t_n \}$ with $|T| = n$. All vertex $t_i \in T$, have a parent $t_{i-1}$ and a child $t_{i+1}$, except for $t_1$, the root, that is without parent and $t_n$, the worker, without child. All other $t_i$ are networkers. The edge set $\epsilon$ of T is defined as $\epsilon = \{ e_{t_i,t_{i+1}} | \forall t_i \in T \}$.

The desired network structure from the root robot to a worker robot is specified with the minimum number of required communication links $C_n$. For a given $C_n$, we enforce $C_n$ number of connectivity chains linking root and worker. The root robot stays near a ground station (or the operator) and acts as a reference point for the chain construction. The worker robot reaches the desired target to fulfill a task (detection, transport, video transmission, etc.) while staying connected through the networkers.

**Corollary to Theorem 1**: Given a connectivity chain $T$ defined in Definition 1, a parent-child relationship exists between all networker robots of a chain, at any given $t_i \in T$, if the change in position $\Delta x_i$ satisfies the condition in Equ. (7) or Equ. (8) for all parent-child pairs, depending on its neighborhood, the robots in the chain will always remain connected.

## IV. Method

This section details the two main modules of the controller: the path planner and the chain connectivity algorithm. The former can be replaced with most path planners: we use the well-known RRT* in this paper. The latter is the implementation of the model shown in Section III.

### A. Path planner

Given a state space $\mathbb{X} \subset \mathbb{R}^n$ and an obstacle free space $\mathbb{X}_f \subset \mathbb{X}$, the problem of computing an optimal path $\pi^*$ from the starting state $x_0 \in \mathbb{X}_f$ to a goal state $X_G \in \mathbb{X}_f$ is well-studied [7], [26]. In this work we select RRT* to compute...
the baseline path for our chain construction by setting the solver objective to minimize path length.

For the path planner workspace, we consider two types of robots: 1. ground robots with a state space \( X \subset \mathbb{R}^2 \) on the ground and 2. flying robots with a state space \( X \subset \mathbb{R}^3 \).

We assume the map of the environment is known. The path planner first tests the existence on the ground plane of a valid path to the desired goal state \( X_G \), based on a simplified version of the algorithm proposed in [27]. To estimate the existence of a path, the state space \( X \) is decomposed into grid cells of resolution \( R \), and the grid cells are labeled as free \( \mathbb{X}_f \) or occupied (obstacle) \( \mathbb{X}_{obs} \). A tree is built out of the free grid cells with \( x_0 \) as the root of the tree. A depth-first search for grid cells containing \( X_G \) is performed. If \( X_G \) is found, then a path exists, raising the flag \( PE \). If a path exists, then both ground robots and flying robots can be used for chain construction, a path \( \pi \) is computed using a state space \( \mathbb{R}^2 \). If the path does not exist on the ground plane, then the RRT\(^*\) planner is used again, this time on the state space \( \mathbb{R}^3 \). The resulting path has a portion, \( \pi_g \subset \pi \), that can be traveled by ground robots. We obtain this portion from the projection of the 3D path \( \pi \) on the ground plane.

### B. Chain Construction algorithm

**Algorithm 1 Chain Construction algorithm**

```plaintext
1: procedure STEP
2:   if no root then
3:     Elect root
4:   end if
5:   for each \( i \in \) Target list do
6:     if no worker for target \( i \) then
7:       Elect new worker
8:     end if
9:   end for
10:  (\( \pi, PE, \pi_g \)) ← Stigmergy.get()
11:  if Worker then
12:     if ¬(\( \pi, PE, \pi_g \)) then
13:       (\( \pi, PE, \pi_g \)) ← Compute path
14:       Stigmergy.put(\( \pi, PE, \pi_g \))
15:     end if
16:     if ¬Check Traversability(\( PE, \pi_g \)) then
17:       Elect new worker(\( PE, \pi_g \))
18:     else
19:       if Parent==root & chain growth required then
20:         Elect new networker(\( PE, \pi_g \))
21:       end if
22:       u ← compute movement(\( \pi \))
23:     end if
24:     else if Networker then
25:       if (\( \pi, PE, \pi_g \)) then
26:         if Parent==root & chain growth required then
27:           Elect new networker(\( PE, \pi_g \))
28:         end if
29:         u ← compute movement(\( \pi \))
30:       end if
31:     end if
32:     apply RVO and set velocity(\( u \))
33: end procedure
```

Algorithm 1 details the pseudo-code of the chain construction. This algorithm was implemented in Buzz [28], a programming language for robot swarms, which eases behavior design efforts by providing several swarm programming primitives. We used the base classes of Open Motion Planning Library (OMPL) [29] to implement our RRT\(^*\) planner as a Buzz function. At launch, a gradient like algorithm [30] serves to elect root and worker robot for each of the given targets, as mentioned in line 7. The gradient algorithm is implemented using virtual stigmergy [31], a primitive available in Buzz. The virtual stigmergy is a tuple based shared memory between robots: once a tuple is written by any robot, it can be accessed from all other (direct or indirect) connected robots.

The worker robot checks for the existence of a path tuple \( \langle \pi, PE, \pi_g \rangle \), if it does not exists, it computes the path, as mentioned on line 13. Once the path (2D or 3D) is computed, the tuple is shared within the virtual stigmergy, as shown on line 14. In this tuple, \( \pi \) represents the path defined as a sequence of states. As explained in the previous section, the variable \( PE \) and \( \pi_g \) represents which type of robots (ground and flying) can traverse \( \pi \) and which portion of \( \pi \) can be traversed by ground robots, respectively. From the obtained path (locally or remotely) the robot determines which part of \( \pi \) it can travel to, following its locomotion type. If the already elected worker type is not appropriate, it elects an appropriate robot type to serve as a worker, as shown on lines 16 - 17. The main loop checks whether the chain should add more robots to reach the target. If yes, a new networker is elected, as mentioned on lines 19 and 26. Finally, the motion command is computed by both networkers and workers (not the root) using the available path and respecting the constraint in 7 and in 8 following their neighborhood. The robots that do not belong to any chain are called free robots, and they will wait close to the root until they get elected as a worker or a networker. The movement commands are altered by a collision avoidance algorithm. Most reactive decentralized collision avoidance can be used here. We selected the Reciprocal Velocity Obstacle (RVO) [32]. The resulting control law is:

\[
u = \begin{cases} u_{path}(\pi, \text{forward}) + u_{rvo} \quad & \text{if } d_p \leq d_s \\ u_{path}(\pi, \text{backward}) + u_{rvo} \quad & \text{if } d_p > d_s \end{cases}
\]

where \( u_{path}(\pi, \text{forward}) \) computes velocity commands moving the robot towards the target and \( u_{path}(\pi, \text{backward}) \) computes velocity commands moving the robot towards the root respecting the constraints in [7] and [8]. In other words, a chain retracts if a parent is in the critical zone of the robot and expands otherwise.

### C. Self-Healing

Furthermore, robots in a chain are aware of the connectivity tree \( T \) and the depth of \( T \) only through local broadcast messages. To compute \( T \) locally, every robot in the chain broadcasts two types of messages: 1) the parent strand: a sequence of IDs built from the root towards the worker. Each robot receives the strand from its parent and appends its own ID before sending it to its child; 2) the child strand: a sequence of IDs, built in the opposite direction of the parent strand: from worker to root. This way, every robot can reconstruct the tree \( T \) and estimate the depth of the tree, simply by concatenating the parent and child strand.
information. If a robot in the communication path fails, the communication chain is broken and the strand cannot be completed. In this case, the parent and the child of the failed robot will attempt to bridge the broken link by navigating toward each other. In this work, we consider robot failures only as a robot inability to communicate or to be detected on the network by its neighbors.

V. EXPERIMENTAL EVALUATION

A. Simulation

We assessed the performance of the algorithm using ARGoS3 [33], a physics-based simulator with Khepera IV and quadcopter models, and 3 maps from a motion planning benchmarking dataset [34]: 1) small (dragon age/arena), 2) medium (dragon age/den203d), and, 3) large (dragon age/arena2). The algorithm and robot controllers were implemented in Buzz. We performed two sets of simulations, one for scalability and one for robustness to individual failures. Each scenario was repeated 30 times with uniform random robot placements around the start point. We obtained a path by running the planner for a fixed period of 2s and we set the bidding time for the gradient algorithm to be 10s for our experimental evaluations. For these simulation experiments, we set the parameters to $d_c = 9.5m$, $d_e = 9.7m$, $d_b = 10.0m$ and the maximum velocity to $v_{max} = 1.0m/s$.

For the scalability experiments, we used all three arenas but we added a wall crossing the map with a small hole above the ground to force a flying robot to pass, as it can be observed in the left most map of Fig. 3. We used 20 ground robots and 5 flying robots for arena 1, 60 ground robots for arena 2, and 100 ground robots for arena 3. For each of the arenas, we enforced 1, 2, and, 3 communication links, except for the 100 robot runs (arena 3) covering only 2 and 3 links. Fig. 4 shows how the robots stay within the safe communication zone of both parent and child, even when navigating narrow corridors. Fig. 5 plots the time taken by robots to build 1, 2, and, 3 links in each of the the arenas. The bottom lines show the reference traveling times computed using the path length, the maximum velocity of the robots (set to 1 m/s) and neglecting all obstacles. It is evident that the time taken to build a chain increases with the size of the arena. Moreover, there is a slight increase in time when increasing the number of links, explained by local collision avoidance. For the 25 robot scenarios, the average time to reach the target were $328.7s$, $421.4s$ and $467.8s$ for 1, 2 and 3 links, respectively.

In a second set of experiments we injected random robot failures at every control step with a random occurrence probably of $p = 0.0005$ and bounded to a maxi-
mum percentage of robots failures $F$ from the set $F \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6\}$, with $0 \leq F \leq 1$.

Fig. 4 shows the first arena, with robot locations and several failed robots on one of the simulation with $F=0.6$ and 3 links. Despite a large number of robots in the chain failing, parent and child of the respective chain bridged the connection and elected new robots to expand the chain. Fig. 5 shows the time taken to build the chain with injected robot failures. Robot failure up to $F=0.3$ does not have significant impact on the algorithm time performance. With more failures, the time required increases as well as the performance variability, with an average maximal time of 865s and a standard deviation of 413.1s for $F=0.6$.

B. Real robot experiments

We validated the performance of our implementation using a small group of 6 Crazyflies\footnote{https://www.bitcraze.io/crazyflie-2/} (flying robots) and 7 Khepera IV [35] (ground robots). We performed experiments in three different settings with two different arena configurations as shown in Fig. 7: 1) 7 ground robots in arena 1 (Ground robots run), 2) 3 ground robots and 3 flying robots in arena 2 (Heterogeneous run), arena 2 has a wall containing a hole before the target and can be only reached by a flying robot, 3) 6 flying robots in arena 2 (flying robots run). The ground robots were equipped with an 800MHz ARM Cortex-A8 Processor and were running an instance of the Buzz Virtual Machine (BVM) on-board to perform both control and path planning. Whereas the Crazyflies were using PyBuzz, a groundstation-based decentralized hardware-in-the-loop controller. A PyBuzz instance is associated to each UAV, receives all the sensory inputs from it, and performs the control step to compute the actuation commands and sends them back to the UAV. The infrastructure is detailed in [36]. Localization is obtained from a motion capture camera system. For these experiments, we set the parameters to $d_s = 1.2m$, $d_c = 1.4m$, $d_b = 1.5m$ and the maximum velocity to $v_{max} = 1.5m/s$.

Fig. 7 shows one of the 10 test runs we performed in each of the three different settings. The figure shows the starting point, the trajectory, and the end position of the robots. On all runs the robots were able to build a communication chain and reach the target, even when it requires a robot to pass through a window.

The box plot in fig. 8 shows the time required by the robots in each setting to build the communication chain and reach the target. Ground robots took on average 100s to reach the target with a wider variability (from 80s to 150s). Heterogeneous team were faster than the ground team with a median time around 50s. Finally, the flying robots were the fastest with a median around 40s and very narrow variability. The holonomic motion of the UAVs makes them more agile at similar velocity, explaining the fastest travel time and narrow variability. The supplementary video\footnote{https://youtu.be/HdueQhKV33I} features an excerpt of these three settings.

VI. CONCLUSIONS

We presented a communication chain construction algorithm for a heterogeneous swarms of robots. Our approach is completely distributed: it requires only relative and local information from neighbors. To tackle robot failures, we exchange information and bridge the chain as soon as it is broken. We assess the algorithm performance with extensive simulations up to 100 robots in three realistic arenas. Real robot experiments with flying and ground robots demonstrate the usability and robustness of the approach. In future works, we will extend the approach to add online re-planning and chain construction, to apply the algorithm conjointly with SLAM strategies.

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REFERENCES

[1] M. Brambilla, E. Ferrante, M. Birattari, and M. Dorigo, “Swarm robotics: a review from the swarm engineering perspective,” Swarm Intelligence, vol. 7, no. 1, pp. 1–41, Mar. 2013.

[2] A. F. Winfield and J. Nenbrini, “Safety in numbers: Fault tolerance in robot swarms,” International Journal on Modelling Identification and Control, vol. 1, no. ARTICLE, pp. 30–37, 2006.

[3] S. Manjanna, A. Q. Li, R. N. Smith, I. Rekleitis, and G. Dudek, “Heterogeneous multi-robot system for exploration and strategic water sampling,” in 2018 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2018, pp. 1–8.

[4] C. Sampedro, A. Rodriguez-Ramos, H. Bavle, A. Carrio, P. de la Puente, and P. Campoy, “A fully-autonomous aerial robot for search and rescue applications in indoor environments using learning-based techniques,” Journal of Intelligent & Robotic Systems, Jul 2018.

[5] L. Giuggioli, I. Arye, A. Heiblum Robles, and G. A. Kaminka, From Ants to Birds: A Novel Bio-Inspired Approach to Online Area Coverage. Cham: Springer International Publishing, 2018, pp. 31–43.

[6] V. S. Varadharajan, B. Adams, and G. Beltrame, “Failure-tolerant connectivity maintenance for robot swarms,” arXiv preprint arXiv:1905.04771, 2019.

[7] S. Karaman and E. Frazzoli, “Sampling-based algorithms for optimal motion planning,” International Journal of Robotics Research, vol. 30, no. 7, pp. 846–894, 2011.

[8] J. Panerati, L. Gianoli, C. Pinciroli, A. Shabah, G. Nicolescu, and G. Beltrame, “From swarms to stars: Task coverage in robot swarms with connectivity constraints,” in 2018 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2018, pp. 7674–7681.

[9] A. Gasparri, L. Sabattini, and G. Ulivi, “Bounded control law for global connectivity maintenance in cooperative multirobot systems,” IEEE Transactions on Robotics, vol. 33, no. 3, pp. 700–717, 2017.

[10] R. Aragues, C. Sagues, and Y. Mezouar, “Triggered minimum spanning tree for distributed coverage with connectivity maintenance,” in Decision and Control Conference (CDC-ECC), 2011 50th IEEE Conference on. IEEE, 2011, pp. 988–993.

[11] M. Schuresko and J. Cortés, “Distributed tree rearrangements for reachability and robust connectivity,” in International Workshop on Hybrid Systems: Computation and Control. Springer, 2009, pp. 470–474.

[12] P. D. Hung, T. Q. Vinh, and T. D. Ngo, “Hierarchical distributed control for global network integrity preservation in multirobot systems,” IEEE Transactions on Cybernetics, pp. 1–14, 2019.

[13] K. Stay, “Using situated communication in distributed autonomous mobile robots,” Proceedings of the 7th Scandinavian Conference on Artificial Intelligence, pp. 44–52, 2001.

[14] Y. Li, Z. Littlefield, and K. E. Bekris, “Sparse methods for efficient asymptotically optimal kinodynamic planning,” Springer Tracts in Advanced Robotics, vol. 107, pp. 263–282, 2015.

[15] L. Zhang, Y. Kim, and D. Manocha, “A simple path non-existence algorithm using c-obstacle query for low dof robots,” Proc. Int. Workshop Alg. Found. Robot.(WAFR), pp. 1–16, 2006.

[16] M. Brambilla and G. Beltrame, “Buzz: An extensible programming language for heterogeneous swarm robotics,” in International Conference on Intelligent Robots and Systems. IEEE, October 2016, pp. 3794–3800.

[17] I. A. Sucan, M. Moll, and L. E. Kavraki, “The open motion planning library,” IEEE Robotics & Automation Magazine, vol. 19, no. 4, pp. 72–82, 2012.

[18] R. Aragues, C. Sagues, and Y. Mezouar, “Distributed tree rearrangements for reachability and robust connectivity,” in International Workshop on Hybrid Systems: Computation and Control. Springer, 2009, pp. 470–474.

[19] M. Schuresko and J. Cortés, “Distributed tree rearrangements for reachability and robust connectivity,” in International Workshop on Hybrid Systems: Computation and Control. Springer, 2009, pp. 470–474.

[20] R. Aragues, C. Sagues, and Y. Mezouar, “Distributed tree rearrangements for reachability and robust connectivity,” in International Workshop on Hybrid Systems: Computation and Control. Springer, 2009, pp. 470–474.

[21] P. D. Hung, T. Q. Vinh, and T. D. Ngo, “Hierarchical distributed control for global network integrity preservation in multirobot systems,” IEEE Transactions on Cybernetics, pp. 1–14, 2019.

[22] K. Stay, “Using situated communication in distributed autonomous mobile robots,” Proceedings of the 7th Scandinavian Conference on Artificial Intelligence, pp. 44–52, 2001.

[23] Y. Li, Z. Littlefield, and K. E. Bekris, “Sparse methods for efficient asymptotically optimal kinodynamic planning,” Springer Tracts in Advanced Robotics, vol. 107, pp. 263–282, 2015.

[24] L. Zhang, Y. Kim, and D. Manocha, “A simple path non-existence algorithm using c-obstacle query for low dof robots,” Proc. Int. Workshop Alg. Found. Robot.(WAFR), pp. 1–16, 2006.

[25] M. Brambilla and G. Beltrame, “Buzz: An extensible programming language for heterogeneous swarm robotics,” in International Conference on Intelligent Robots and Systems. IEEE, October 2016, pp. 3794–3800.

[26] I. A. Sucan, M. Moll, and L. E. Kavraki, “The open motion planning library,” IEEE Robotics & Automation Magazine, vol. 19, no. 4, pp. 72–82, 2012.

[27] M. Rubenstein, A. Cornejo, and R. Nagpal, “Programmable self-assembly in a thousand-robot swarm,” Science, vol. 345, no. 6198, pp. 795–799, 2014.

[28] C. Pinciroli and G. Beltrame, “Buzz: An extensible programming language for heterogeneous swarm robotics,” in International Conference on Intelligent Robots and Systems. IEEE, October 2016, pp. 3794–3800.

[29] I. A. Sucan, M. Moll, and L. E. Kavraki, “The open motion planning library,” IEEE Robotics & Automation Magazine, vol. 19, no. 4, pp. 72–82, 2012.

[30] M. Rubenstein, A. Cornejo, and R. Nagpal, “Programmable self-assembly in a thousand-robot swarm,” Science, vol. 345, no. 6198, pp. 795–799, 2014.

[31] 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 BIONETICS), ser. BICT’15. ICST, Brussels, Belgium, Belgium: ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2016, pp. 287–294.

[32] J. Van den Berg, M. Lin, and D. Manocha, “Reciprocal velocity obstacles for real-time multi-agent navigation,” in 2008 IEEE International Conference on Robotics and Automation. IEEE, 2008, pp. 1928–1935.

[33] 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-engine simulator for multi-robot systems,” Swarm Intelligence, vol. 6, no. 4, pp. 271–295, 2012.

[34] N. Sturtevant, “Benchmarking for grid-based pathfinding,” Transactions on Computational Intelligence and AI in Games, vol. 4, no. 2, pp. 144–148, 2012.

[35] J. M. Soares, I. Navarro, and A. Martinoli, “The khepera iv mobile robot: Performance evaluation, sensory data and software toolbox,” in Robot 2015: Second Iberian Robotics Conference. Springer, 2016, pp. 767–781.

[36] R. Cotsakis, D. St-Onge, and G. Beltrame, “Decentralized collaborative transport of fabrics using micro-uavs,” in IEEE/RSJ International Conference on Robotics and Automation (ICRA), 2019.