RASS: Risk-Aware Swarm Storage

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Abstract—In robotics, data acquisition often plays a key part in unknown environment exploration. For example, storing information about the topography of the explored terrain or the natural dangers in the environment can inform the decision-making process of the robots. Therefore, it is crucial to store these data safely and to make it available quickly to the operators of the robotic system. In a decentralized system like a swarm of robots, this entails several challenges. To address them, we propose RASS, a decentralized risk-aware swarm storage and routing mechanism, which relies exclusively on local information sharing between neighbours to establish storage and routing fitness. We test our system through thorough experiments in a physics-based simulator and test its real-world applicability with physical experiments. We obtain convincing reliability, routing speeds, and swarm storage capacity results.

Index Terms—Swarm Robotics, Information Sharing, Robot Safety

I. INTRODUCTION

Using multi-robot systems for the exploration of unknown environments is very appealing. Indeed, if robots do not overlap in their exploration task, the amount of terrain covered increases proportionally with the number of robots in the system [1]. This can, for example, be particularly useful for search and rescue scenarios [2] where the speed at which the environment is covered is of critical importance. However, as the number of robots increases so does the amount of data collected, which puts pressure on the data storage infrastructure. Unfortunately, multi-robot systems usually suffer from unreliable connectivity [3], and directly sending the information to an external storage system (e.g., the cloud) may not always be feasible. An alternative to overcome this issue is using the swarm of robots as means of distributed data storage. However, because the robots composing the swarm often have very limited memory and storage capacities, saving large amounts of data across the swarm can prove challenging. Furthermore, the robots in a swarm are not necessarily reliable [4]; even in controlled environments, they are usually meant to be easily replaced. This issue is aggravated when they must face situations that decrease their reliability, such as exposure to dangerous environments like search and rescue scenarios, forest fire reckoning, or nuclear inspection and cleanup. Therefore, giving the robots a way to eventually relay the information they acquired during their mission to a control station for more permanent storage is a definite advantage: it not only allows the information to be stored in a safe location accessible by human operators, it also alleviates the memory usage of the robots and enables continuous operation. Nonetheless, because in practice robots have a finite communication range, the information collected at the periphery of the swarm usually needs to be routed through other robots before reaching a base station. Although forwarding the data through the shortest path towards the base station enables prompt retrieval [5], in real-world scenarios, this approach can be problematic for two reasons: first, such a path might not exist at all, for example if the robots are in an area completely cut off from external communication (e.g. a cave); second, if that path does exist, it might be too dangerous to use. For example, a robot trying to relay information by going through a highly radioactive area might cause a physical failure or data corruption. Furthermore, the base station cannot request the data, as communication with the robots is never guaranteed. Instead, data must be autonomously forwarded to the base station by the robots. For the same reason, and because of the overhead it entails, it is not practical to use leaders to coordinate the storage and routing processes. In addition, the system must take into account that the robots are constantly moving and acquiring new data, meaning that storage and routing conditions are dynamic. These constraints motivate the need for a completely decentralized, risk-aware swarm storage system that can safely and efficiently store data and route it towards a base station in a percolating fashion whenever possible. In this paper, we make the following contributions to multi-robot storage:

- A distributed, dynamic and risk-aware storage system
- A fully decentralized risk-aware routing algorithm

We name the combination of these two contributions RASS: Risk-Aware Swarm Storage. The rest of the article is structured as follows: in section II we present related work and useful concepts upon which we build RASS; in section III we present our system model; in section IV and V we detail our simulations and physical experiments along with their respective results; finally in section VI we draw some conclusions.

II. RELATED WORK AND BACKGROUND

A. Distributed Storage

Distributed hash tables (DHTs) are data structures specifically designed to partition data across a network of storage nodes in a key-value format. They come with a set of issues susceptible of hindering their performance, consistency, and partial connectivity being some of them [3]. The virtual stigmergy presented in [6] tackles the problem using Conflict-free Replicated Data Types (CRDTs) and allowing decentralized robust information sharing for multi-robot systems. This virtual stigmergy is implemented directly into the Buzz programming language [7]. However, in the
virtual stigmergy, each node stores a full copy of the data (in an eventually consistent way). This means it has full redundancy and no partitioning, thus offering good reliability but poor storage capacity optimization.

A memory-efficient storage mechanism designed for multi-robot systems was proposed in SwarmMesh [8]. It uses the available memory of an agent and its connectivity with its peers to generate unique identifiers, which are the basis of its partitioning scheme and which represent an agent’s fitness to store data. Storage of larger items (such as binary files) in DHTs has been studied in [9], where an auction process is used to partition data. Other partitioning systems have been proposed, such as Locality-aware Distributed Hash Tables [10] which posits that routing data through nodes that are close in a network will reduce latency. Therefore, they use information from the nodes’ Autonomous System Numbers (ASNs) to partition data. Geographic Hash Tables [11], Cell Hash Routing [12] and [13] all use position-based information in their partitioning systems, and the second specifically addresses DHT implementation for ad-hoc networks of resource-constrained nodes.

These systems show various metrics that can be used to devise a partitioning system for a DHT. However, none of them takes into account the effects of environmental dangers on the reliability of the distributed storage system. RASS, our decentralized risk-aware storage and routing mechanism, aims to address this issue by including a risk measurement in its partitioning scheme.

B. Risk Assessment

Taking risk into account when designing autonomous systems is of high importance as excessive exposure to risk can lead to system failures. In an unknown environment, risks are usually tied to a certain location. Information about these locations could therefore provide increased situational awareness for robots to effectively perform a given mission. Belief maps and occupancy maps provide this situational awareness by assigning values to cells of a discretized environment. Whereas occupancy maps define the presence or absence of a feature (e.g. fire), beliefs maps assign probabilities to the cells of the discretized environment and usually offer better performance [14]. Belief maps have been extensively used in the past for robotic exploration [15], [16], [17].

A risk-aware exploration algorithm leveraging a belief map of the risk associated with the environment has been recently proposed in [18]. In this work, robots combine efforts in building a shared belief map of the environmental risks and use it to spatially avoid the dangerous pitfalls of the environment. The belief map is used to provide risk awareness to an exploration algorithm which ultimately results in fewer robot failures. In RASS, we seek to use similar shared risk awareness to establish a reliable distributed data storage and routing mechanism, while improving its memory consumption by relying on more localized information.

C. Routing

There exist many types of routing algorithms for wireless sensor networks. For example, packets can be explicitly routed towards a known destination by forwarding messages towards a neighbour which optimizes a given metric. One simple approach is to send messages through the shortest path in terms of Euclidean distance. However, this assumes a complete knowledge of the nodes’ Cartesian coordinates, which is far from realistic in swarm robotics. Indeed, robots might be operating into GPS-denied environments, or they might not even be equipped with GPS at all. A comparative study of metrics for multi-hop wireless networks shows that hop-count performs the best in scenarios where nodes are mobile [19] because it is robust in dynamic topologies [20], which is the case for RASS’s nodes. Notable implementations using this metric are given in [21], [22], [23], which are respectively greedy, power-adaptive, and grid-based routing algorithms. Routing algorithms have also been inspired by biology: some are based on slime molds [24], [25] and others on ant colonies [26], [27]. However, the former category has applications mostly in static topology networks, which makes it ill-suited to our needs. The latter category specifically addresses data aggregation, which is particularly relevant to our objective our percolating data towards a base station.

III. System Model

We consider a fully decentralized multi-robot system tasked with the exploration of a dangerous environment. The multi-robot system is denoted as the collection of agents \( a_i \in A \). We assume the robots to have limited storage and communication capabilities. We also assume the presence of an operator or base station who is interested in collecting the data generated by the swarm. Note that this last assumption does not mean that our system is centralized: it is reasonable to assume that the autonomous system has to produce some value (i.e. data) for the humans deploying it, and the base station does not influence the decision-making process of the swarm, but rather act as an information sink. We consider the amount of data needed to be stored to be greater than the individual storage capabilities of the robots. It is therefore impossible for the individual agents to store a complete copy of the system’s data, but the data can be fully stored by the base station. Also, we consider that the robots are only able to communicate if they are within a certain communication radius \( R \). As a result, if a message needs to be sent to a distant location (e.g. to the base station), it might need to be routed through multiple nodes before reaching the desired destination.

A. Risk Modelling

Radiation is known to cause performance loss and failures in robots [28], [29]. We therefore adapt the risk modelling from [18], which is based on a set of independent point radiation sources \( S \) with individual intensity \( I_j \sim U(0, 1) \). Note that we use radiation as a *model* of risk, but our method could be applied to other sources of danger: vertical air currents, high temperature areas, etc.
Risk is assumed to be dynamic, meaning that the position of the point radiation sources $s_j(t) \in E$ can vary across time. For example, radiation can spread to new areas if radioactive particles are transported by wind. It is important to account for the dynamic nature of risk as it gives the system the capability to adapt to changing environments. We achieve adaptability by having each agent sense the radiation at every time step at its current position. The perceived intensity decays exponentially (with $\lambda$ as a decay parameter) as the Euclidean distance $\rho(x_i)$ between $s_j$ and $x_i$ increases. The total perceived radiation level by a robot $a_i$ at position $x_i \in E$ is given by:

$$r(x_i) = b + \sum_{s_j \in S} \frac{I_{s_j}}{1 + \lambda \rho(x_i)^2}$$  \hspace{1cm} (1)

and is measured by an on-board sensor with Gaussian measurement noise $b \sim \mathcal{N}(0, 0.05)$. We posit the radiation’s effect on the system is to cause data corruption (which is one of its possible effects [29]). Let the probability of the event of a datum $d$ getting corrupted while stored on robot $a_i$ due to an individual radiation source $s_j$ be $P(c_i = 1|s_j) \sim \mathcal{B}(r(x_i), (x_i))$, which follows a Bernoulli distribution. Because we assume that the sources of radiation affect the robots (and thus the stored data) independently, the probability of a datum being corrupted due to the combined effect of radiation sources follows a Bernoulli distribution given by:

$$P(c_i = 1|S) \sim \mathcal{B}(r(x_i)) = 1 - \prod_{s_j \in S} 1 - P(c_i = 1|s_j)$$  \hspace{1cm} (2)

### B. Distributed Risk-Aware Storage

Our risk-aware storage system is built upon three assumptions:

1) Because nodes exposed to a higher level of risk also have a higher failure probability, they should be used less, thus maximizing overall storage reliability

2) Efficiently moving data away from the periphery of the swarm and towards the base station will increase the storage capacity of the system and the persistence potential of the data, because the base station usually has more storage and reliability than the swarm

3) Percolating data from edge nodes to the base station should be done by choosing routes devoid of risk to minimize data loss

From these assumptions, we derive RASS’ two principal mechanisms: the routing table and the fitness-based percolation. We combine them to obtain a high-level algorithm described in Alg. [1][1] in which $\mathcal{N}$ is the set of neighbours of a given agent. Because of the distributed nature of the algorithm and because all robots execute the same code (except the base station), we forego the indices notation to simplify the algorithms.

1) Routing Table: We assume that the swarm can be represented by a connected graph $G$ with nodes $A$ and edges $L$ respectively representing agents and their wireless communication links. In practice, this connectivity cannot be maintained at all times, because of the quality of the links in $L$ and because of the movements of nodes $A$. However, this assumption can be mostly maintained through mechanisms for connectivity maintenance [30] if necessary. Furthermore, the need for this assumption can be relaxed because RASS does not need a constant link with the base station; it can opportunistically move data towards it when possible, and store them locally in the meantime.

Given the existence of at least one (multi-hop) path between any node and the base station, we can establish a routing table based on hop count. Because peer communication is not the focus of this work, the routing table held by each node only contains the minimal hop count between its neighbours and the base station and can therefore be implemented with a hash table. The process to construct and periodically update this table involves exchanging messages between the base station and the nodes as suggested by [31], as we implement in Alg. [2][2] Building a routing table with the aim of prioritizing higher capacity nodes is similar to the Gateway Optimization [32] implemented in the B.A.T.M.A.N mesh networking protocol [33], where in our case the base station acts as a gateway. Assuming a message can only be forwarded to an immediate neighbour within a given time step, the required time to build the routing table in a connected graph is bounded by $\Omega(1)$ and $O(|A|)$ as it takes at most $|A|$ steps to send a message from the base station to the furthest robot in a pathological topology (a line) and 1 step if the network is fully connected. However, in more realistic scenarios such as tree networks or scale-free topologies, building the table can be expected to take on average $O(log|A|)$ steps because of the network’s depth. We implement message forwarding through a gossip algorithm, which allows local broadcasting between robots.

### Algorithm 1: RASS Execution Loop

```plaintext
while True do
  update_routing_table()
  update_fitness()
  if not is_fit() and |N| > 0 then
    evict_data()
  end
  store_measurements()
end
```

### Algorithm 2: Building/Updating the Routing Table

```plaintext
routing_table ← listen_neighbor_hop_count()
if id = 0 then
  min_hops ← 0
else
  min_hops ← min(routing_table)
end
broadcast(min_hops + 1)
```
2) Potential-Based Percolation: Our risk-aware storage system draws inspiration from SwarmMesh [8], in that each node periodically assigns itself a potential \( \phi_i \) based on its fitness to store data, given by:

\[
\phi_i = \begin{cases} 
\frac{1}{a h_i + \beta r_i(x_i)} & \text{if } m_i > 0 \\
0 & \text{otherwise} 
\end{cases} \quad (3)
\]

where \( m_i \) is the memory available on node \( i \), \( r_i \) is the risk associated with the current node’s location (stored in the distributed belief map) and \( h_i \) refers to the minimum hop count required to reach the base station from \( i \) as specified in the routing table. Parameters \( \alpha \) and \( \beta \) are respectively the routing weights and risk weights, which allow adapting the policy based on the relative importance of the routing time and the environmental, risk with respect to each other. Similarly to [8], a node which becomes unfit to store data will evict such data by moving it into its routing queue. The condition for “unfitness” is simply:

\[
T \phi_i < \max_{j \in \mathcal{N}} \phi_j \quad (4)
\]

where \( \mathcal{N} \) and \( T \) are the set of \( i \)'s neighbours and the fitness threshold, respectively. The latter’s purpose is to ensure data is transferred only when the neighbours’ max fitness is significantly higher than \( \phi_i \) to avoid instability and overhead which would result from frequent and inefficient transfers. This fitness policy causes data to naturally percolate along the edges towards the base station because nodes with a higher potential are both closer to it and located in safer areas. When necessary, data is evicted using a Least Recently Used (LRU) policy and transmitted to the fittest neighbour.

IV. SIMULATIONS

A. Experimental Setup

We ran extensive simulations in a physics-based simulator, ARGoS [34] with models of Khepera IV [35] robots to eliminate the effect of potential hardware issues on the conceptual validity of our system and also to verify that it scales well to large swarm sizes. We executed 30 simulation runs with 100 robots for each type of experiment to reach conceptual validity of our system and also to verify that it scales well to large swarm sizes. We executed 30 simulation runs with 100 robots for each type of experiment to reach results with low uncertainty. The robots are placed within a 20m by 20m arena and their communication radius \( R \) is set to 3m. Three (3) radiation sources are randomly distributed in the environment around the origin. The base station is located in a corner of the arena and its storage capacity is assumed to be infinite.

In order to replicate realistic operation scenarios, we chose to artificially introduce bandwidth limitations. In all experiments, robots can only exchange up to 10 data items at every time step. For the same reason, our simulated robots have a limited storage capacity of 50 data items of at most 50 bytes each, as the data are simple items such as small tables or floating-point numbers. This gives a total storage capacity of 2500kb per robot. Because the robots can only exchange up to 20% of their stored data at a given time step, it amounts to a bandwidth of 0.5kb/s. Data are generated by each robot at fixed out of phase intervals.

To evaluate the performance of our system in different scenarios, we tested it with static topologies: a grid-like formation, and a scale-free network; as well as with dynamic topologies: a formation obtained through Lennard-Jones potential interactions and a formation evolving from random walk motions. Testing with static topologies allows us to verify applicability with fixed wireless sensor networks relevant to IoT applications, while experiments with dynamic topologies are more relevant for mobile robotics applications.

To setup RASS, we used values of \( \alpha = 10 \) and \( \beta = 1 \) in Eq. [3] because risk measurement values are normalized between 0 and 1 while hop-count values are typically upper-bounded to 10 (for 100 robots). Our first benchmark algorithm is to use a fitness policy based purely on hop count, i.e. if required, data is sent only to neighbours closer to the base station. Our second comparison baseline is to store data in a virtual stigmergy (a CRDT) [6]. Using the virtual stigmergy practically ensures that no data can be lost due to corruption because it is fully replicated across the system. The first metric we used in our performance evaluation is reliability, expressed as \( \frac{n_g - n_l}{n_g} \), where \( n_g \) and \( n_l \) are respectively the amount of data generated and lost at every time step. The second metric is the average data transfer speed, measured as the delay between the creation of a given datum and its arrival by percolation to the base station. We excluded results of this metric for the virtual stigmergy, as the stigmergy cannot include the concept of a base station (since all nodes are peers), and stigmergy propagation speeds are detailed in [6]. The third metric is the evolution of the system’s total storage capacity over time, i.e. the amount of data stored by the agents and the base station combined.
Fig. 3: 400m² environment in the ARGoS simulator with 100 KheperaIV robots in a formation obtained through Lennard-Jones potential interactions.

Fig. 4: 400m² environment in the ARGoS simulator with 100 KheperaIV robots in a formation obtained through random walk motions.

B. Results

The results obtained in the 30 simulation runs for the static topologies (grid-like and scale-free) as well as for the dynamic topologies (Lennard-Jones potential and random walk) are presented in Figs. 5, 6, 7 and 8 respectively.

Results show that RASS outperforms the hop-count algorithm in terms of reliability. Because of the risk awareness component included in its fitness policy as detailed in Eq. 3, robots do not always route the data through the shortest path to the base station. RASS avoids the dangerous storage nodes of the system when routing data which explains the higher reliability levels displayed in Fig. 5a, Fig. 6a, Fig. 7a and Fig. 8a. This is why, on average, RASS takes 54.89% more time to route the data to the base station when compared to the hop-count algorithm. The shortest path might not always be the safest one; RASS will take an alternate route if the risk associated with the shortest one is too high. On the other hand, the hop-count algorithm always takes the shortest path towards the base station regardless of the risk associated with it. This leads to a higher number of data losses due to corruption and an overall lower reliability. However, hop count can yield faster transfer speeds as shown in Fig. 5b, Fig. 6b, Fig. 7b and Fig. 8b.

For the virtual stigmergy, most of the data losses can be attributed to the storage having reached its maximum capacity. Indeed, because of the fully replicated nature of the stigmergy, the memory of the agents is quickly saturated. Table I shows that on average, across the 500 steps of the simulations runs, the virtual stigmergy has 100% of the individual memories used. This means that the nodes of the system are simply full and cannot store data anymore. In comparison, RASS uses between 1% and 2% of the local memories of the nodes, and hop-count is even lower at values around 0.5%. This full redundancy prevents losing data from corruptions. However it entails a very inefficient use of the memory of the robots and ultimately leads to data losses due to insufficient memory capacity. The result is an unchanging storage capacity over time and poor reliability as shown in Fig. 5a for the virtual stigmergy strategy.

The low values of local memory usage shown in Table I for RASS and hop-count were obtained because the topologies used to test the algorithms were usually well connected in accordance with the connected graph assumption we made in III-B.1. For the most part, multiple routes were connecting the nodes to the base station and as a result, the collected data was routed towards the base station instead of being kept locally. Such a result implies that the system, by maintaining a low individual storage occupancy, allows the robot to adapt to situations in which they would be temporarily stranded: if their storage were to be mostly full, they would not be able to generate new data without promptly losing it. This storage buffer thus allows them to continue collecting data while being temporarily disconnected from the rest of the swarm.

V. PHYSICAL EXPERIMENTS

A. Experimental setup

We evaluated RASS’ performance with the same metrics on physical robots to confirm the real-world applicability of our system. We used 5 small drones in a controlled indoor environment. These drones use standard Raspberry Pi Zeros as their main computer, meaning they have relatively low capabilities, and are therefore well suited to verify our algorithm. We designed a static topology with one drone acting as a base station and 4 others acting as agents. The radiation source (red cone) in Fig. 9 is positioned to make one of the paths more dangerous, allowing us to verify if data is routed in the longer but safer path. The communication range is set to 1.5m. The topology is illustrated in Fig. 9.

| Topology       | Algorithm  | Transfer speed (hops) | Memory used (%) |
|----------------|------------|-----------------------|-----------------|
| Grid-like      | RASS       | 11.45                 | 1.35            |
|                | Hop-Count  | 9.11                  | 0.61            |
|                | Stigmergy  | N.A.                  | 100.00          |
| Scale-Free     | RASS       | 11.44                 | 1.95            |
|                | Hop-Count  | 6.85                  | 0.50            |
|                | Stigmergy  | N.A.                  | 100.00          |
| Lennard-Jones  | RASS       | 12.51                 | 1.69            |
|                | Hop-Count  | 7.32                  | 0.51            |
|                | Stigmergy  | N.A.                  | 100.00          |
| Random Search  | RASS       | 12.68                 | 1.67            |
|                | Hop-Count  | 7.76                  | 0.57            |
|                | Stigmergy  | N.A.                  | 100.00          |
Fig. 5: Performance comparison of RASS, hop count and stigmergy in a static grid-like topology.

Fig. 6: Performance comparison of RASS, hop count and stigmergy in a static Scale Free topology.

Fig. 7: Performance comparison of RASS, hop count and stigmergy in a dynamic Lennard-Jones topology.

Fig. 8: Performance comparison of RASS, hop count and stigmergy in a dynamic random search topology.
assess RASS’ performance, we compared it with a hop-count algorithm over 3 runs.

Fig. 9: Topology of the 3x3m environment with 4 drones, a base station and a radiation source used in the physical experiments.

B. Results

The reliability results of the physical experiments conducted on the drones are presented in Fig. 10. They show that RASS outperforms the hop-count algorithm in terms of reliability which lead to overall greater swarm storage. Even if the topology used to assess the performance of our algorithm was simple and the number of agents in the system was limited, the physical experiments confirm the real-world applicability of RASS. Using only local interactions, it was able to choose safer paths for the data to be routed through which resulted in fewer data corruptions.

Fig. 10: Evolution of reliability over time on the the physical experiments

VI. CONCLUSIONS

We presented RASS, a Risk-Aware Swarm Storage system in which a swarm of robots can collectively store data on strategically chosen members. This choice is made without central coordination and is purely based on local information shared between the robots. This information is simply composed of risk measurements and topological distance from a robot to a base station, and used to determine a robot’s fitness to store data as well as to establish the most reliable and fast route towards the base station.

We show in our experiments that RASS largely outperforms a hop-count-based solution as well as a virtual stigmergy in terms of reliability and total swarm storage capacity, while only being slightly slower in terms of percolation speed compared to the hop-count-based algorithm. RASS showed good scalability in physics-based experiments as it repeatedly performed well with a large number of robots. It performed well in experiments on physical robots.

An interesting direction for future work could be to conduct experiments in more diverse scenarios, for example in search and rescue applications where image storage and processing is required, therefore increasing the system’s workload.

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