ROSE: Random Opportunistic and Selective Exploration for Cooperative Edge Swarm of UAVs

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***Abstract*—In this work, we propose a physical approximation scheme – Random Opportunistic and Selective Exploration (ROSE) – for aerial localization of survivors by using a collaborative swarm of IoT-based unmanned aerial vehicles (UAVs). The UAV swarm performs a simultaneous multi-pronged search of a given zone by dividing the search region among the swarm members. This multi-pronged search strategy speeds-up the search, and the division of search areas among the swarm members avoids redundant exploration of an already explored location. As the communication range of the member UAVs is limited, the swarm members communicate opportunistically among themselves to share the information of the visited sites. We formulate the various probabilities associated with opportunistic communication of these aerial IoT nodes and simulate the performance of the approximation algorithm based on these formulations. Simulation results of the proposed approach successfully locate 100% of the ground targets within an acceptable time-frame, and out-performs established searching schemes such as the truncated Levy walk, frontier-based search, and sweep search.**

***Keywords*—Cooperative computing, Opportunistic communication, UAV Swarm, Random walk, Optimal Search theory, Aerial IoT Network.**

I. Introduction

Unmanned aerial vehicles are being used extensively for surveillance and search-and-rescue operations owing to their ability to quickly gain access to remote locations, and their capability of attaining high coverage speeds during aerial search operations. It is mainly due to these factors that UAVs are being rapidly adopted for aerial communication relaying, and post-disaster management operations [1]. Searching within a realistic time-frame during post-disaster rescue efforts has enormous societal implications as it directly translates to saving human lives – shorter the search time, higher is the chance of maximizing ground-survivor rescue. Considering an $n \times n$ search area on the ground, which are sub-divided into smaller grids of size $L_G \times L_G$, with randomly located targets n_S (as represented in Fig. 1), a single UAV-based search of this grid will accumulate a worst-case time complexity of $O(n^2)$. The use of a single UAV for searching over a large area is not only time-consuming but puts excessive strain on the UAV's power resources.

The coverage of a massive search area is better undertaken by the use of multiple UAVs at the Edge itself instead of offloading data to a central system [2]. The use of intra-communicating UAV swarms for ground-target/survivor detection is considered more efficient regarding reduced redundancies in target/survivor detection. The Edge UAVs in the swarm are a part of a network and communicate with each other to divide the search region among themselves, resulting in a significant reduction of the overall mission time. The search zone is typically divided into grids, which can be directly mapped to real-world GPS coordinates.

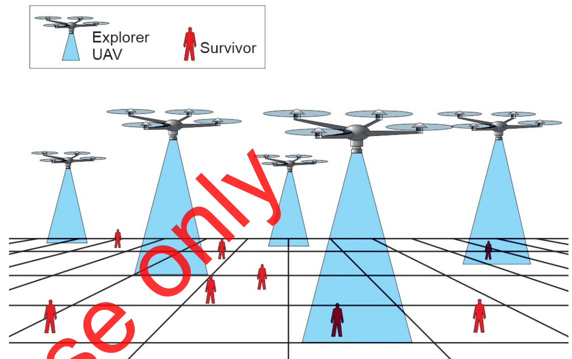


Figure 1. The implementation scenario showing UAV groups searching for ground survivors in a gridded search area.

For a n_D UAV system, we consider a set of UAVs $U = (u_1, u_2, u_3, \cdots, u_{n_D})$ searching for randomly spread unknown number of ground survivors within the $n \times n$ search zone. For an i^{th} grid location in the search zone denoted by g_i, the i^{th} UAV follows a path $p^i = (g_1, g_2, g_3, \cdots, g_j), \ni g_j \leq n^2$, as shown in Fig. 2(b) in order to locate survivors in its path p^i. Let P denote the sum of all visited grids found by the set of all paths covered by the set of UAVs U in order to locate maximum survivors within the search zone, such that

$$P = \{p_1, p_2, p_3, \cdots\}, \quad \ni p_1 \cap p_2 \cap p_3 \cap \cdots = \emptyset \tag{1}$$

For an i^{th} UAV visiting $m(u_i)$ grid locations during its mission time, P is generalized as

$$P = \sum_{i=1}^{n_D} \sum_{k=1}^{m(u_i)} k_i, \quad \ni P \leq n^2 \tag{2}$$

Let n_S denote the set of all survivors in all the grid locations such that the i^{th} grid location in the search area has n_s^i survivors associated with it. Here, n_S can be represented as $\{n_s^1, n_s^2, n_s^3, \cdots, n_s^{n^2}\}$. It is noteworthy to mention that each n_s^i can have zero survivors ($n_s^i = 0$), one survivor ($n_s^i = 1$), or more than one survivor ($n_s^i > 1$) associated with it. Considering this, the total survivors n_S is generalized for the whole search zone as $n_S = \sum_{i=1}^{n^2} \sum_{k \in \mathbb{R}_0^+} k_i$. However the UAVs have limited energy (e), which gradually depletes with time (t) owing to the energy required to keep the platforms airbone. The collective energies of all the UAVs simultaneously performing the search within the search area at t is considered to be $E(t)$, and is represented as $E(t) = \sum_{i=1}^{n_D} E_i(t)$.

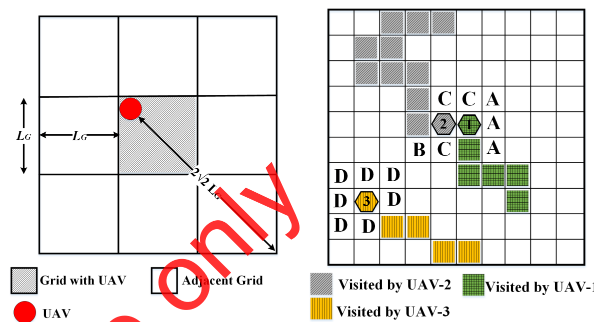
A. UAV Swarm-based Aerial Exploration

In this work, we consider n_S randomly distributed ground targets/survivors within an $n \times n$ search area. n_D UAVs are assigned to visually locate all the ground targets/survivors within the search area. It is assumed that all the UAVs participating in the search have the common map of the search area. It is also assumed that the maximum communication range of a UAV is limited to the nearest neighbor grid only, especially as the IoT-enabled communication is typically low-power and hence, has low-range. Considering, each grid in the search area to be equilateral with side L_G, the communication range R_{comm} of each UAV is restricted to $R_{comm} = 2\sqrt{2} \times L_G$, as shown in Fig. 2(a). We define the terms – Exploration Time, Average Exploration Time, and Redundant Exploration – concerning this work in Definition 1.

Definition 1. *Exploration Time σ is the total time taken by a UAV to mark all the visited grids and is used interchangeably with the term – mission time – throughout this work. Average Exploration Time is the average of σ of each of the deployed n_D UAVs, and is denoted by $\bar{\sigma}$, such that $\bar{\sigma} = \frac{\sum^{n_D} \sigma}{n_D}$. Finally, Redundant Exploration is the act of exploring an already explored grid.*

In Fig. 2(b), we consider three UAVs marked 1, 2, and 3 attempt to search all the grids. The grids already covered by the UAVs within the search zone are shaded. Subsequently, from its current position, UAV-1 has the choice of selecting its next grid to be visited from grids marked **A** or **C**. Similarly, UAV-2 can choose from grids marked **B** or **C**, and UAV-3 can choose from grids marked **D**. As soon as two UAVs are in R_{comm} of each other, and a choice has to be made by multiple UAVs regarding the selection of a single grid, a priority-based UAV selection is applied. This selection allows one of the UAVs to choose the next location to visit, subsequently leading the other UAVs to choose from the grid options remaining. However, it is to be noted that we do not focus on the priority-based UAV selection in this work and instead hard-code the priorities of the UAVs according to their sequence numbers. We additionally assume the concept of dual velocities for the UAVs – Exploration velocity ($v_{explore}$), and Skip velocity (v_{skip}) – such that $v_{explore} << v_{skip}$. Aerially searching a grid for ground targets/survivors requires processing the obtained visual data by the UAV's cameras, so the value of $v_{explore}$ is limited by the UAV's processing speed instead of the UAV's kinematic constraints. However, to skip through an already explored grid, the UAV travels at its maximum stable velocity.

We additionally restrict the relative motion of the survivors within a grid. Furthermore, we approximate their movement to be relatively static in comparison to the motion of the UAVs within a given frame of time such that for Δ_s distance covered by a survivor, and Δ_{UAV} distance covered by a UAV in time t, $\Delta_s << \Delta_{UAV}, \forall\ t \in \mathbb{R}^+$. In continuation, considering the total exploration time σ of a UAV within a grid of dimensions $L_G \times L_G$, and survivor velocity within the grid μ, we define the upper boundary of μ, such that $\mu \times \sigma < L_G$.



(a) Communication range limits (b) Grid coverage by the UAVs

Figure 2. Functional outline of the communication and traversal followed by the UAVs.

Having restricted the motion of the survivors to a search grid, we consider that the delay in video processing, which is mainly attributed to the low-power IoT processor on-board the UAV, and information generation within the UAV $v_{explore}$ takes considerable time to complete in each grid. It can be safely stated that either reducing $v_{explore}$ or reducing the number of grids to be visited by each UAV will speed-up the survivor detection within the given search area. In this work, we consider $v_{explore}$ to be fixed and defined by the UAV's processor. The only option of rapid detection of survivors is reducing the grids to be visited by the UAVs, which is again bounded by constraints of energy and UAVs used.

Definition 2. ***Survivor Detection Ratio (SDR):*** *We define Survivor Detection Ratio (SDR) at time τ as the ratio of number of survivors detected collectively at time τ to total number of survivors n_S.*

B. Random Exploration in Opportunistically Communicating UAV Swarms

We consider multiple IoT-enabled UAVs are searching for survivors within the search area, which start-off at random boundary grids and are independent of each other. The UAVs opportunistically share information whenever they are in R_{comm} of each other. The swarm forms an aerial IoT network in which all the possible communication links between the nodes are not active all the time, which is an attempt to reduce energy consumption. The communication link between two aerial nodes is activated when they are in proximity to each other. This communication scheme is opportunistic, and the information exchange updates the already visited paths on the search-area memory maps present with the UAVs so that redundant exploration is avoided once the information transfer is completed between the UAVs. Each UAV has a search region matrix (search-area grid map), in which all the grids are initially marked unvisited. The UAV marks the current grid being visited and then randomly chooses the next grid out of the nearest available unvisited grids. The information about a UAV's visited grids is reflected in the other UAVs as soon as they come within R_{comm} of each other. This scheme ensures the maximization of the mutual exclusiveness of UAV-wise grid coverage, and reduction of redundant exploration. Similar to the concept of dual velocity, we also assume the dual mode of UAV operation – *Exploration mode*, and *Communication mode*. Initially, all UAVs start in the exploration mode and subsequently move from one grid to another searching for survivors. As soon as all the grids are marked visited, the UAVs become static and enter into the communication mode in which they only communicate with the UAVs in their vicinity. To summarize, we propose an approach of multiple UAV-based aerial searches for survivors, which follow a random exploration pattern and employ opportunistic communication [3] to update each other about the grids already covered in the search area.

II. Related Works

UAVs are being increasingly deployed for aerial search and tracking of ground-based targets in domains such as surveillance, disaster management, border security, wildlife monitoring and remote mapping. Various approaches have been deviced for standalone [4] as well as collaborative UAV swarm based tracking [5] of the ground as well as aerial targets. Approaches for UAV-based tracking of ground targets include Gaussian mixture models for prioritizing search subregions and task difficulty maps for incorporating partial information [4], geometric relations [5], revisit time based cooperative tracking [6], decision logic based radio beacon detection, graph-based search [7], and others [8]. Tasks related to tracking such as trajectory and path planning of UAVs also require innovations to consider the energy onboard the UAVs and fasten the tracking process. Approaches to UAV path planning such as Monte Carlo tree search and factored belief vectors [9] play crucial roles in optimizing features of UAV-dependent solutions. Additional approaches such as congestion and delay-aware planning algorithms for highly mobile platforms [10] and self-organization mechanisms in decentralized UAV swarms [11] provide much-needed support to the task of UAV-based tracking of ground targets.

UAVs flying in a symmetrical formation towards an objective typically follow time-varying inter-agent distance-based communication approaches [12]. Harder problems include multiple UAVs working in a decentralized manner to accomplish a task cooperatively. Approaches such as critical coordination information sharing and cooperative scheduling [13] show promising results. Trajectory optimization based approaches are also used for maintaining communication in UAV networks or even between UAVs and ground base stations [14]. However, this severely restricts the possible communication performance, which in turn, can be addressed by approaches such as variable rate relaying [15].

The UAV search and communication approaches have dependencies either on the communication infrastructure or the prior knowledge of inter-UAV distances in a formation. This dependence results in reduced dynamism and less adaptiveness in our considered scenario for most of the approaches. The lack of a fixed reference/communication infrastructure also results in increased information update delays and information redundancies, which our proposed solution intends to address.

III. System Model

We analyze the problem scenario theoretically and mathematically before simulating the solution. We consider a $n \times n$ grid space in which k UAVs are deployed, which we represent as $D = \{d_1, d_2, d_3, ..., d_k\}$. The UAVs start the search operation from different grids and cover paths making sure it does not search the same grid again. The information of the visited grids, however, is initially local and contained only with the UAV visiting it. When two UAVs come within communication range, they exchange their information of the visited grids, and then the total available search space reduces for both UAVs. So, information of one UAV, in this case, is not globally available to all the other UAVs. The information is shared probabilistically instead, as shown in Algorithm 1. Considering, each UAV has its local information of visited and unvisited grids, let the number of grids unvisited by UAV d_i be denoted by $u_i(t)$.

Considering that the UAVs interact for the r^{th} time at $t = \omega_r$, we can represent the unvisited grids for the two UAVs as $u_1(t) = u_1(\omega_r) - t$ and $u_2(t) = u_2(\omega_r) - t$, $\forall t \in [\omega_r, \omega_{r+1})$. At $t = \omega_r$, the set of grids covered by d_1 is N_r^1 and that by d_2 is N_r^2. Additionally, the number of grids globally visited by the UAVs d_1 and d_2 at $t = \omega_r$ is denoted by v_r such that

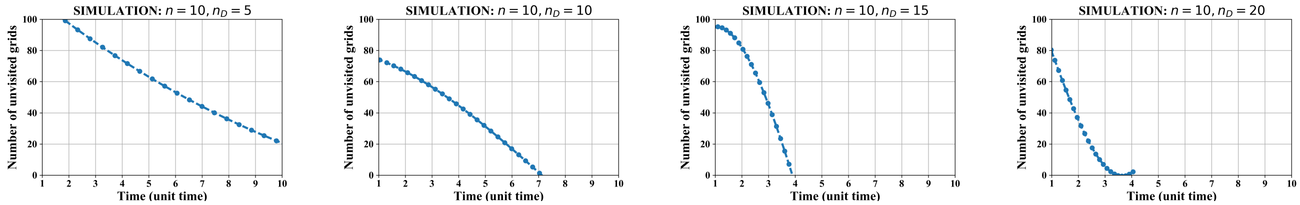
$$v_r = |N_r^1 \cup N_r^2|, \quad 0 < v_r \le n^2 \tag{3}$$

Subsequently, the number of unvisited grids for the UAVs d_i at $t = \omega_r$ becomes $u_i(\omega_r) = n^2 - v_r$, which can be reformulated as $u_1(t) = n^2 - v_r - t$ and $u_2(t) = n^2 - v_r - t$ $\forall t \in [\omega_r, \omega_{r+1})$. We now consider a set $S = \{(t_i, v_i) \mid i \in \mathbb{R}^+\}$, the elements of which follow the property $\omega_r < \omega_{r+1}$ and $v_r \le v_{r+1}$. Eventually, the number of unvisited grids for an opportunistically communicating UAV d_i is formulated as

$$u_i^{opp}(t) = n^2 - v_r - t, \quad \omega_r \le t < \omega_{r+1} \tag{4}$$

A. Methodology

This section outlines the methodology followed by the UAVs in the search area during its exploration task. The system is initialized by marking all the grids in the UAVs' in-memory map of the search area as unvisited. Subsequently, some UAVs start the random exploration of the area from randomly selected directions (outwards to inwards) along the



(a) $n_D = 5$ (b) $n_D = 10$ (c) $n_D = 15$ (d) $n_D = 20$

Figure 3: Grid coverage progress for varying UAVs (n_D) in a 10×10 search area with 20 survivors randomly distributed within it.

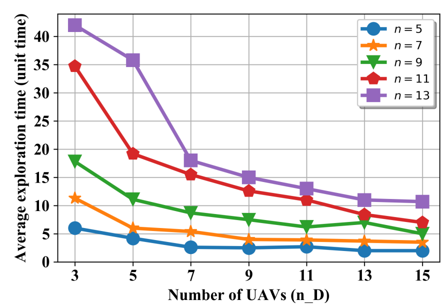
Algorithm 1 Random Exploration and Opportunistic Communication module for each UAV.

```
G_current ← random grid within bounded region
Mark G_current visited
MODE ← Exploration
while MODE = Exploration do
    if all grids are marked visited then
        Record Exploration Time
        MODE ← Communication
    end if
    if G_current ≠ G_next then
        Travel to G_next
        G_current ← G_next
        Mark G_current visited
    end if
    Search for survivors in the current location
    if Drones are available for communication then
        Exchange information with drones with lower drone ID
        within communication range
        if G_current = G_next then
            G_next ← nearest unvisited grid
        end if
        Exchange information with drones with higher drone ID
        within communication range
    else
        if G_current is fully explored then
            G_next ← nearest unvisited grid
        end if
    end if
end while
while MODE = Communication do
    exchange information with drones within communication
    range
end while
```

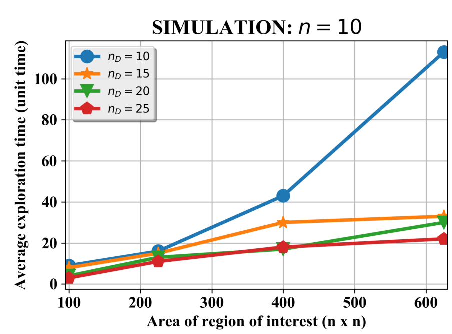
boundary of the search area. Each visited grid is marked in the in-memory map of the UAV visiting it, following which the UAV moves to another grid within the search area. The selection of the next grid is made only once while the UAV is in its current grid. If, while in a grid, the decision for the future grid selection has not been made, and if the UAV comes in the range of another UAV, a decision jointly based on the priority of the UAVs. As soon as all the grids of the search area are marked visited, the UAV switches to the communication mode in which it keeps hovering within the last visited grid. The information is relayed to other UAVs opportunistically. Algorithm 1 outlines the explained process of the proposed ROSE scheme. This algorithm is simulated in Python. UAV classes and functionalities are separately defined, and simulation for multiple UAVs is performed on parallel threads. This parallelism is incoporated to provide a more realistic simulation environment that goes through different states simultaneously for various UAVs in the search area. The parallel threads which were centrally monitored to extract performance metrics for parameters such as n, n_D, n_S, T_e and T_s.

IV. Performance Evaluation

We evaluate and analyze the performance of the proposed ROSE-based scheme against the following metrics – *Grid coverage progress*, *Average exploration time*, *Survivor detection ratio*, *Information exchanges*, and *Progress of first interaction time*. Finally, we compare the performance of our scheme against the exploration approaches of *Frontier-based exploration*, and *Sweep search*.



(a) Variations in number of UAVs



(b) Variations in search region

Figure 4: Average exploration time of the proposed approach (ROSE).

A. Grid Coverage Progress

We first analyze the grid coverage progress of ROSE with a given number of UAVs in a search region of a fixed area, keeping the number of UAVs n_D and grids $n \times n$ fixed. To study the coverage progress, we plot the number of unvisited grids against time as shown in Fig. 3. The slope of the plotted curve provides the estimate of the measure of the speed of exploration of the grids – steeper the slope faster is the exploration speed. In Fig. 3(a), for $n_D = 5$ in a 10×10 implementation area, the change in the number of unvisited grids is prolonged, which eventually becomes 0 beyond the scope of the plot window. Subsequently, in Figs. 3(b), 3(c) and 3(d), the slope of the curve rapidly increases and the unvisited grids rapidly drop to 0 for increased number of UAVs. This increase in the slope implies that the exploration speed increases, which is practically impossible as the UAV velocities are limited during exploration. This behavior, in turn, can be attributed to the information exchanges from other UAVs which have visited a set of grids not visited by the current UAV. We previously predict this behavior in Theorem I-B.

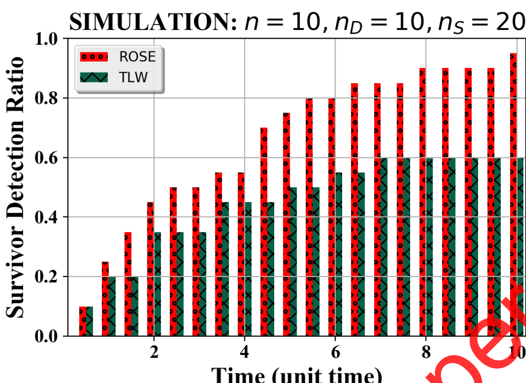


Figure 5: Performance of ROSE and TLW concerning Survivor Detection Ratio using 10 UAVs in a 10×10 search area with 20 randomly distributed survivors.

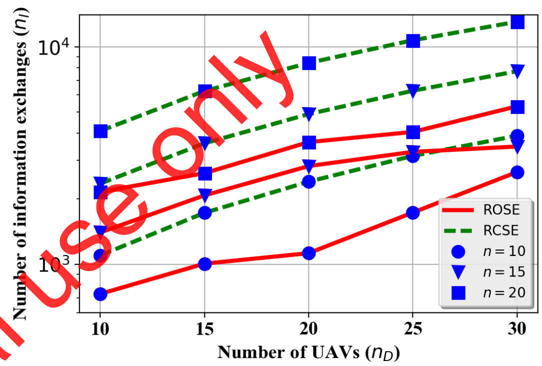
B. Average Exploration Time

In continuation, we vary the search grid size $n \times n$ and the number of UAVs n_D to study the trend in average exploration time σ. The evaluation of average exploration time is done to estimate the speed of detection of the survivors, collectively by the group of UAVs. We compare our algorithm (ROSE) with Truncated Levy Walk (TLW) [16] with minor modifications to incorporate the grid matrix layout of the search region in it. We then substitute the opportunistic network in ROSE with a centralized network in which a UAV transmits information to the coordinator node, which then relays it to other UAVs. We term this centralized approach Random Centralized Selective Exploration (RCSE).

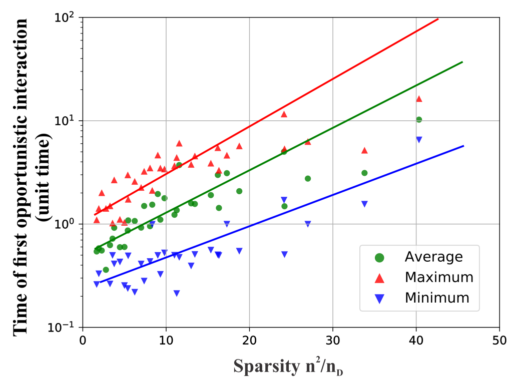
We observe that the average exploration time is directly proportional to the area of the search region ($\bar{\sigma} \propto n^2$) and inversely proportional to the number of UAVs deployed ($\bar{\sigma} \propto 1/n_D$). From Figs. 4(a) and 4(b), as the primary workload of the exploration process is the area of the search region, increasing the area takes more time whereas, increasing the number of UAVs decreases the resultant workload for each UAV, thereby decreasing the exploration time.

C. Survivor Detection Ratio

From Fig. 5 it is observed that ROSE searches the survivors faster compared to TLW. We attribute this behavior to the much lesser redundant explorations performed by the UAVs as compared to the TLW. The ROSE's opportunistic data update at the UAVs, although slower than TLW is quickly compensated through lower chances of exploring already explored grids, resulting in ROSE outperforming TLW concerning survivor detection over more extended periods of time.



(a) Information Exchanges



(b) Interactions vs. sparsity

Figure 6: Comparison of the proposed opportunistic (ROSE) and a centralized (RCSE) communication approaches with respect to – a) information exchanges, and 2) time of first interaction.

D. Information Exchanges

We consider the count of exchanges occurring between the UAVs for updating information of visited grids and detected survivors as the number of information exchanges n_I. The UAVs in the proposed ROSE exchange information opportunistically, while in RCSE, the information is exchanged by a UAV each time it chooses its next grid. Under these conditions, we compare the values of n_I in ROSE and RCSE for varying values of n and n_D as shown in Fig. 6(a). We observe that ROSE outperforms RCSE for the same number of UAVs and search area. The UAVs in ROSE undergo lesser information exchanges, which in-turn signifies lesser energy consumption for overall data transfer.

E. First Interaction Time Progress

In Fig. 6(b), we observe that as the distribution of UAVs in the search region becomes sparse (lesser UAVs within a search area), the time measured from the beginning of operation for two UAVs to interact increases exponentially. As the probability of interaction of two UAVs inversely proportional to the area of the search region, Fig. 6(b) signifies that increasing the sparsity (n^2/n_D) above a certain threshold (20 in our case) will significantly increase the operational time of the system as a whole. The trend for maximum, average and minimum interaction times are similar.

F. Comparison with Existing Schemes

This work primarily builds-up on survivor detection, which necessitates faster response times for locating ground survivors. We focus firstly on the average exploration time as the primary parameter in evaluating the performance of the proposed ROSE algorithm. We compare the performance of ROSE against RCSE and TLW regarding the average exploration time by varying the number of UAVs n_D. Finally, we compare the performance of ROSE to existing approaches regarding average exploration time and changes in the number of side grids n.

Firstly, we compare the σ vs. n_D for ROSE against RCSE and the benchmark approach of TLW. In Fig. 7 we observe that $\bar{\sigma}$ for RCSE is of the same order as ROSE. In continuation, RCSE takes the least time while TLW takes the most. As the information in RCSE is updated more frequently compared to ROSE, $\bar{\sigma}$ values for RCSE are lower than that for ROSE. However, the reason for such high values of $\bar{\sigma}$ for TLW stems from the fact that much time is wasted in redundant explorations by the UAVs. The performance of our proposed ROSE is marginally better than the RCSE approach. However, as ROSE does not depend on fixed communication infrastructures and scheduling, the advantages of dynamicity and robustness far outweigh the benefits of marginally better average exploration time for RCSE.

We have additionally compared our proposed ROSE with two existing exploration techniques – 1) *Frontier-based exploration*, and 2) *Sweep search*. In Frontier-based Exploration [17], [18] the explorers move to the frontiers to explore the remaining portion of the map, and do not go back to the visited grids – an approach similar to ours, albeit without opportunistic information exchanges. The in the other approach of Sweep Search or Parallel Exploration [19], the explorers sweep through the search area in parallel paths and repeat the process for unexplored regions. As we mainly target minimizing the exploration time, we consider σ as the performance metric for comparison. Theoretically, the best case performance of the Sweep Search is $\lceil n/n_D \rceil n$, and that of ROSE is n^2/n_D. Simulation results in Fig. 8 show

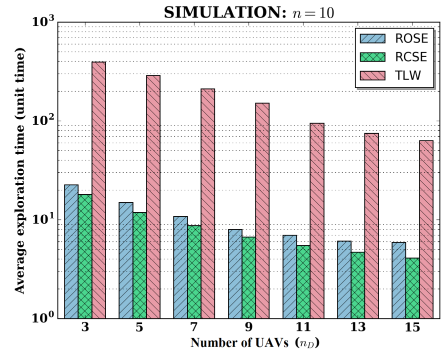


Figure 7: Comparison of the average exploration times for ROSE, RCSE and TLW in a 10×10 search area with 10 UAVs and 20 randomly distributed survivors.

that ROSE is approximately five times faster than Frontier-based exploration for all values of n. Additionally, ROSE is marginally poorer than Sweep search for lower values of n, which becomes comparable for higher values of n.

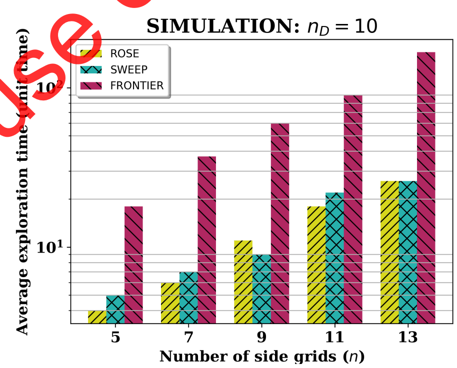


Figure 8: Comparison of the average exploration times for ROSE with the established frontier-based search and sweep search in a 10×10 search area with 10 UAVs and 20 randomly distributed survivors.

V. Conclusion

In this work, the proposed cooperative scheme for Edge UAV swarm-based ground survivor detection within a given search area using random exploration by the swarm members and opportunistic communication for information updates shows promising results. During the search for survivors restricted within grid cells in a fixed search area, we observe that our proposed ROSE performs better than approaches such as TLW and Frontier-based search. For larger implementation areas, our approach becomes comparable to approaches such as sweep search. The opportunistic communication in our scheme ensures the exchange of information, but in a minimalistic manner, which in turn reduces redundancies in exploration and translates to the conservation of UAV's energy resources. As ROSE is a decentralized approach for coordination of UAVs within a swarm, which does not need any central coordinator or ground-based communication references, the additional benefits of robustness and dynamicity are always an added advantage in our approach.

In the future, we plan to integrate efficient survivor identification techniques along with our proposed ROSE. Additionally, we plan to implement this on real-life hardware and include the performance of various communication schemes and IoT connectivity protocols, which is estimated to be energy-efficient owing to the nature of the proposed ROSE scheme.

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