



REF: A Rapid Exploration Framework for Deploying Autonomous MAVs in Unknown Environments

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Abstract

Exploration and mapping of unknown environments is a fundamental task in applications for autonomous robots. In this article, we present a complete framework for deploying Micro Aerial Vehicles (MAVs) in autonomous exploration missions in unknown subterranean areas. The main motive of exploration algorithms is to depict the next best frontier for the MAV such that new ground can be covered in a fast, safe yet efficient manner. The proposed framework uses a novel frontier selection method that also contributes to the safe navigation of autonomous MAVs in obstructed areas such as subterranean caves, mines, and urban areas. The framework presented in this work bifurcates the exploration problem in local and global exploration. The proposed exploration framework is also adaptable according to computational resources available onboard the MAV which means the trade-off between the speed of exploration and the quality of the map can be made. Such capability allows the proposed framework to be deployed in subterranean exploration and mapping as well as in fast search and rescue scenarios. The performance of the proposed framework is evaluated in detailed simulation studies with comparisons made against a high-level exploration-planning framework developed for the DARPA Sub-T challenge as it will be presented in this article.

Keywords MAV Sub-T exploration framework · DARPA Sub-T

1 Introduction and Background

Rapid exploration and mapping of unknown subterranean environments have become a significant interest in the field

The REF exploration framework code will be publicly available at <https://github.com/LTU-RAI/REF.git> for the community.

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of autonomous deployment of robots¹. MAVs have the potential in being a viable solution in terms of mining areas inspection [50], exploration and mapping [28, 30, 40] and inspection of infrastructures [33] due to their high degree of freedom and fast traversability. The applications of MAVs have also been discussed in developing next-generation rotor crafts for mars exploration in [38] and [39]. Deploying MAVs for exploration and mapping of dark, dusty, and hostile mines and caving systems is particularly challenging because, at the beginning of the exploration process, the environment is completely unknown for navigation. In order to map surrounding for safe navigation in such environments, vision-only based navigation techniques are insufficient [37]. The unstructured and rocky environment of mines and caves is a major challenge that contributes to uncertainty in sensor measurements [1]. In an attempt to explore and map such environments, the crucial requirements for autonomous navigation problems are a) detecting the frontiers, b) selecting the optimal frontier, and c) safe navigation to the selected frontier to successfully build a map of the environment.

¹ The video link of this work can be found at <https://youtu.be/nmN0Xy6EqLM>

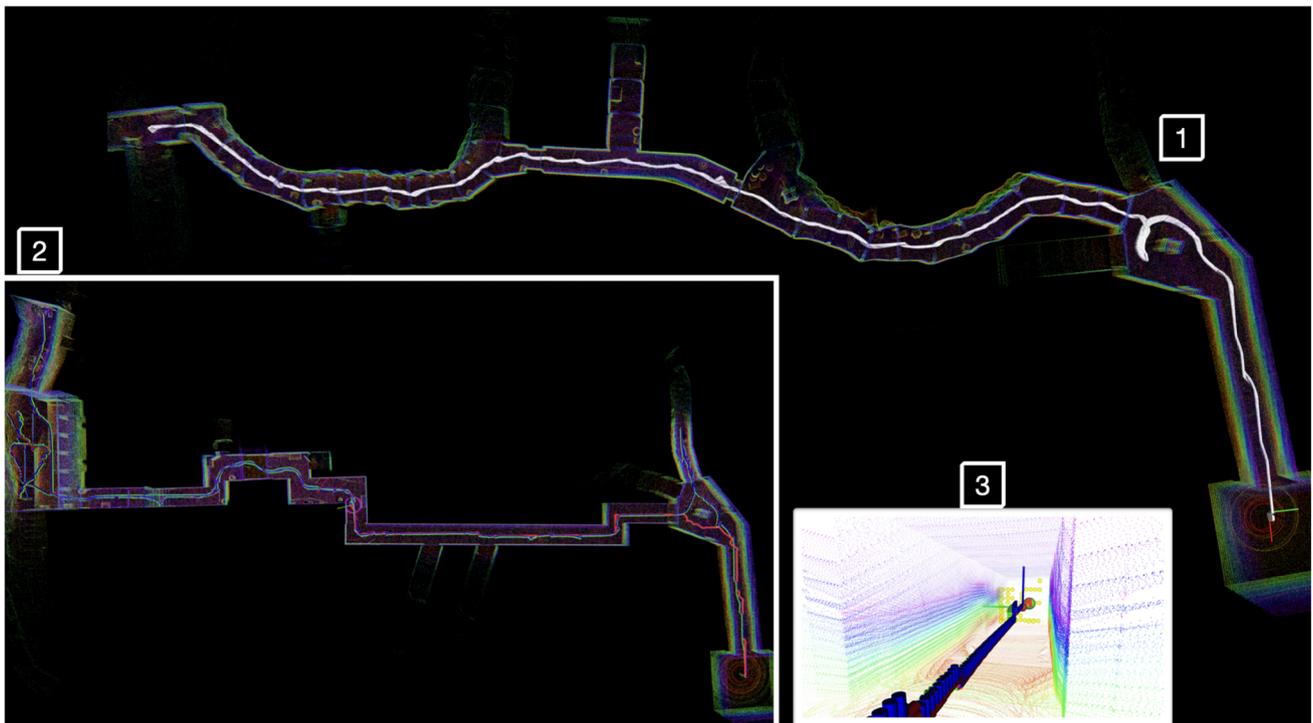


Fig. 1 DARPA Sub-T world: Exploration instance. (1) Rapid local exploration behavior (2) local exploration in very narrow as well as wide cave-void like areas (3) Safe Next Best Frontier (NBF) in obstructed narrow tunnels

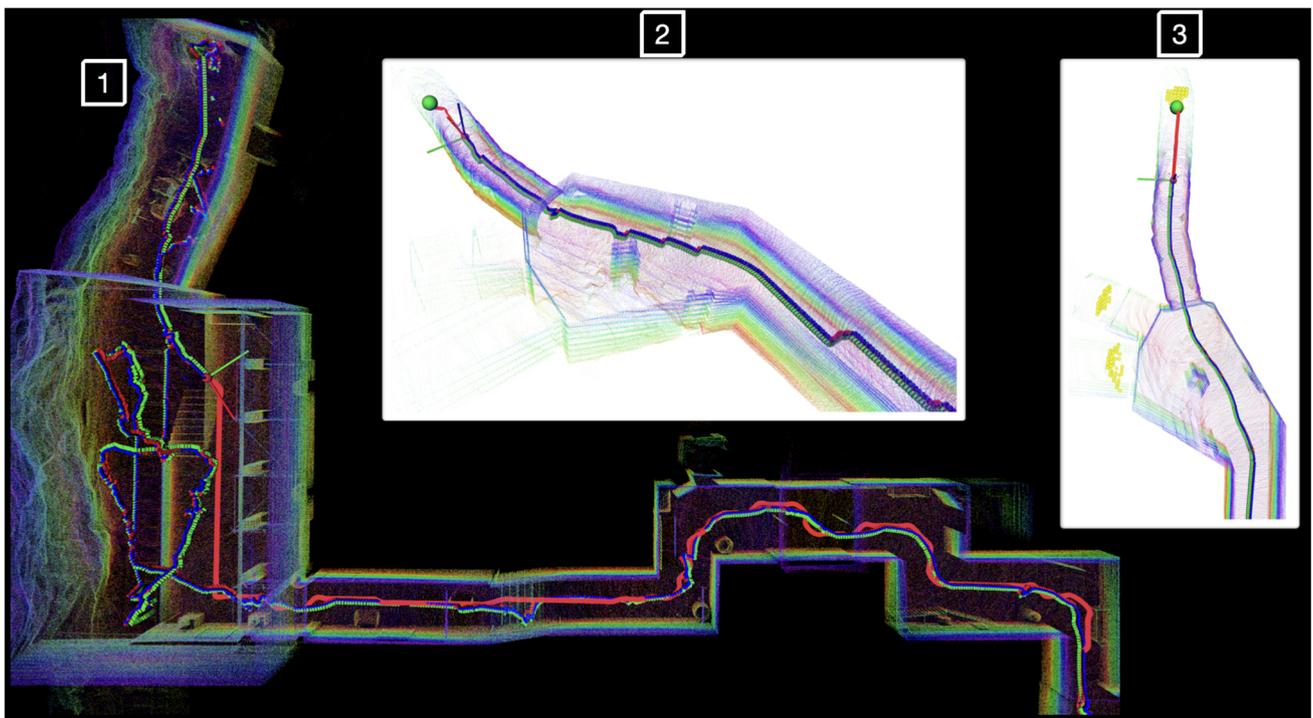


Fig. 2 Exploration behavior using the proposed framework in multiple exploration scenarios in DARPA Sub-T virtual world

In Figs. 1 and 2 exploration instances of the proposed method is shown in different environments. The capability of the proposed method to handle the exploration of narrow passages as well as wide tall void-like structures is presented through Fig. 2.

The framework introduced in this work selects optimal frontiers based on the idea of continuing the exploration in one direction until there is no new potential information to gain in the particular direction. Planning a safe path to such selected frontiers is crucial when exploring a large environment. The path planning method used in this work takes into account the safety margin of such paths based on the size of the MAV and its ability to traverse through the obstructed areas. The MAVs are also constrained in terms of their limited time of flight. Therefore the proposed framework also accounts for cost-based frontier selection while evaluating the next optimal area to visit. The proposed framework also complements the idea of efficiently utilising the resources of the vehicle by rapid yet safe navigation. This work presents a rapid exploration framework for safe autonomous navigation of MAVs in caves. The point cloud map of the explored virtual cave environment with the MAV's trajectory is presented in Fig. 3.

1.1 Related Works

In the original work of frontier-based exploration [54], the points lying at the boundary between known (free) space and unknown space are defined as frontier points. In [54] a closest frontier from the robot's position is selected to move to such that the boundary at which frontiers lie, will also progress

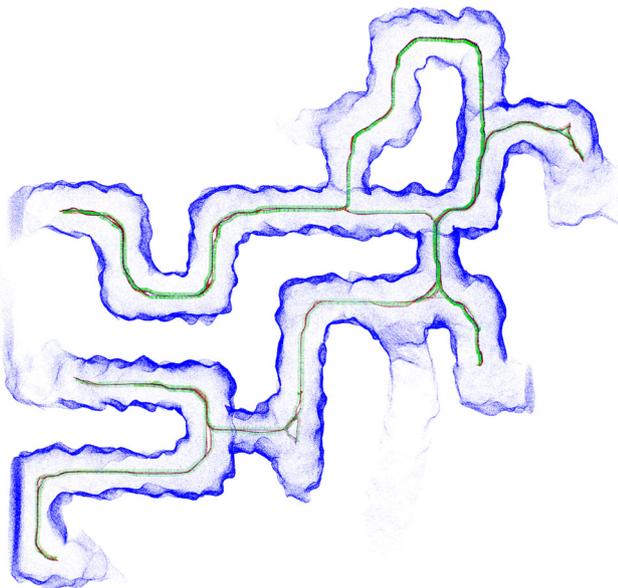


Fig. 3 MAV risk-aware trajectory while exploring a wide-large cave environment using the proposed approach

towards more unexplored space. The same approach was also extended for the case of multiple robots, as presented in [55]. In [21] and [23] frontier-based exploration strategies are studied extensively for comparison against different exploration approaches. A 3D Frontier Based Exploration Tool (FBET) for aerial vehicles is presented in [58]. The FBET framework uses a similar approach to [54] for frontiers generation and the generated frontier are clustered for the selection of candidate frontier goal based on cost function that takes into account the cost of moving to the goal point. A Stochastic Differential Equation (SDE) based exploration approach is presented in [46]. In the SDE-based exploration strategy, the authors consider simulating the expansion of the system of particles with Newtonian dynamics for the evolution of SDE. In [46] the authors consider the region showing a significant expansion of particles as a region that would lead the MAV to more unexplored space. In [19] A vision-based exploration-mapping problem-solving technique is presented that also utilizes MAV to navigate in unexplored areas using continuously updating frontiers. Exploration of unknown environments is also extended to legged or ground robots. Probabilistic Local and Global Reasoning on Information roadMaps (PLGRIM) as presented in [26], discusses a hierarchical value learning strategy for autonomous exploration of large subterranean environments. The methodology presented in [26] uses hierarchical learning to address local and global exploration of large-scale environments while focusing on near-optimal coverage plans. A Frontloaded Information Gain Orienteering Problem (FIG-OP) based strategy is presented in [41] that uses topological maps to plan exploration paths in fixed time budget exploration scenarios. The method presented in [41] is tested with ground robots in a multi-kilometers subterranean environment targeted at time-constrained exploration missions.

Separated from frontier-selection methods are the methods with integrated exploration behavior in the path planning problem, often based on trying to plan a path in order to maximize the information gain while minimizing distance traveled or similar metrics. These planners generally fall under the Next-best-view approaches as in [4, 9, 42] and have seen great application success, but other methods in similar directions exist, such as ERRT [28] takes into consideration also actuation effort along with information gain in order to yield more efficiency towards the exploration of unknown and unstructured areas. Additionally, the Rapid exploration method proposed in [7] is developed to maintain a high MAV velocity while exploring. Autonomous inspection of structures by utilizing a frontier-based algorithm, along with a Lazy Theta* path planner, is presented in [17]. Finally, an information-driven frontier exploration method for MAV, which uses a hybrid approach between control sampling and frontier based is presented in [8]. As state-of-the-art exploration method presented in [12] is tai-

lored and deployed in large-scale exploration missions both in simulations and real-world experiments. The developed planner is structured around motion primitives that search for admissible paths, taking advantage of efficient volumetric mapping with collision checks and future-safe path search that evaluates the variation of speed along the path, while also maximizing the exploration gain for an overall fast navigation scheme. Moreover, in [45] an exploration approach that combined frontiers with receding horizon next-best-view planning has been proposed. The frontiers are part of the global planning part, while the next best view is responsible for the local exploration part. In [53] a dynamic exploration planner (DEP) for MAV exploration, based on a Probabilistic road map has been presented. The sampling nodes are added incrementally and distributed evenly in the explored region, while the planner uses the Euclidean Signed Distance Function map to optimize and refine local paths. The exploration scheme in [5] presented the Permutohedral Frontier Filtering, which is based on bilateral filtering with permutohedral lattices to extract the score-based spatial density of the selected frontiers. Multiple studies have also incorporated visual servoing-based path planning and control architectures for mobile robots as presented in [13]. The authors in [16] have formulated gaussian functions based control architecture for mobile robots that rely on mainly visual information of surroundings. The authors have extended the work further in [14] that uses decision trees as well as adaptive potential area methods to achieve autonomous control of mobile robots in real life applications. In the field of sampling-based space mapping area the research studies presented in [15], use the bi RRT method to smooth the RRT path using curve fitting methods. In [15] the Ability to navigate from start to goal position using the smooth path by curve fitting also addresses the problem of actuation of robot if extended for MAV in future.

Various planning algorithms have been developed for the navigation of aerial platforms in unknown environments, where in general they can be divided into map-based or memory-less approaches or their combination. In [44] a hierarchical planning framework that combines map building from fused depth data, as well as instantaneous depth data, both organized into separate K-D trees has been proposed. The planner relies on a slower global planner to get a goal location, which is evaluated using motion primitives against the K-D trees with the lowest cost candidate primitive to be selected. In [56] a motion planning method for fast navigation of autonomous MAVs has been developed. The algorithm divides the environment modeling in two parts: i) the deterministically visible area within the onboard sensor range, and ii) the probabilistically known area beyond the sensor range from a-priory map. The planning method maximizes the likelihood of reaching a goal, where a finite set of candidate trajectories are separated into groups and

evaluated for collisions. In [34] a navigation method for MAVs based on disparity image processing has been proposed. More specifically, the disparity image is used for direct collision checking, incorporating C-space expansion of obstacles. The motion planning part verifies obstacle-free trajectory, projecting them into the disparity image and comparing their disparity values with the C-space disparity values for collision checking. In [6] a memory-less planner that is partitioning free space in pyramids, using direct depth image measurements has been demonstrated. The use of spatial generation of pyramids of the free spaces, allows for labeling obstacle-free trajectories that lie inside the pyramids, while achieving fast generation of large number of candidate trajectories and performs collision checks. In [2] the authors present a reactive navigation system for MAV exploration. The proposed algorithm is based on a two-layered planning approach that leverages occupancy information for frontier detection and local raw LiDAR data for collision avoidance based on artificial potential fields. In [49] "FASTER" has been developed, an optimization-based planning approach for fast and safe motion in unknown environments. The planner leads to high-speed navigation by allowing to plan in known and unknown configuration space using a convex decomposition in a two-trajectory design approach, a fast and safe trajectory. In [32] a reactive navigation and collision avoidance scheme for MAVs that combines a layer of obstacle detection based on 2D LiDAR with NMPC constraints was proposed for agile local navigation. In [24] a collection of sensor-based heading regulation methods have been proposed for aerial platform navigation along underground tunnel areas. In this work, the heading regulation methods using i) image centroid calculation from either single image depth estimation, or dark area contour extraction, or CNN for dark area extraction and ii) from processing 2D lidar measurements have been described. In [18] a mapping for motion planning architecture that queries for the minimum-uncertainty view of a point in space, searching a set of recent depth measurements under noisy relative pose transforms has been presented. This work enables the identification of local 3D obstacles in the presence of significant state estimation uncertainty, evaluating motion plans. Table 1 summarizes the SoA exploration strategies while highlighting the contribution of REF.

1.2 Motivation

The proposed Rapid Exploration Framework is developed in alignment with the exploration part of the problem statement in DARPA subterranean challenge. The challenge required team of robots to navigate in a completely unknown subterranean environment to detect artifacts of interest and localize them in the global map. Aerial vehicles provide additional flexibility when traversing through narrow entrances, par-

Table 1 Different exploration frameworks and their corresponding exploration-planning approach

| Framework | Exploration approach |
|-----------|---|
| [54] | Closest frontier based on euclidean distance and navigation to selected frontier based on depth-first-search on grid |
| [57] | Incremental frontier structure and hierarchical planning for trajectory generation to selected frontier |
| [58] | Maximize information gain based on travel cost to frontier |
| [7] | Selection of furthest frontier in FOV to maintain high speed flight & switches to classical frontier approach when no frontiers exist in FOV |
| [52] | Exploration derived from direct point cloud visibility to reduce mapping computation |
| [19] | Compute for centroid of closest frontier cluster & polar histogram based computation for cost to reach selected frontier |
| [28] | Sampling based RRT structure approach to maximize information gain with minimizing actuation cost |
| [12] | 3D acceleration sampling to compute collision free paths to maximum volumetric gain vertices using motion primitives |
| [10] | Bifurcated Local and global exploration approach. Sampling based graph for local exploration & global re-positioning to closest |
| [43] | Learning based exploration derived from graph based planning exploration planning architecture. |
| [REF] | Safe frontier generation for local and global exploration & local frontier selection based on heading and avoidance cost & heading regulation, height difference and travel to frontier cost based global re-positioning when local exploration gain is low |

tially blocked passages, and over obstacles. Add to that, their higher navigation speed, the MAVs act as data mules to carry information to and from the base. However, rapidly identifying safe paths for exploration while navigating is a challenging task for such MAVs. In response, this work establishes a framework that prioritizes rapid exploration in one direction until there is not enough information to acquire or a dead end in exploration. A risk aware expendable grid based planning module complements the proposed exploration framework to globally re-position the MAV. The global re-positioning is triggered when MAV meets a dead end of a tunnel or cave and needs to navigate to a potential global frontier vertex to continue exploring a partially seen area. The proposed strategy is different from classical exploration approaches in terms of extracting local safe goals to visit while exploring and risk aware planning in an expendable grid map to quickly globally re-position the MAV. The clas-

sical approaches in literature consider frontiers and sampling based solutions for exploration however, an additional layer of focused local planning assists the MAV to rapidly explore local unknown space while efficiently utilizing the available flying time. The efficient utilization of flying time for MAVs is backed by a rapid exploration behaviour which a) focuses on exploring in one direction to avoid unnecessary change in the heading vector of the MAV and b) plans risk aware paths while navigating forward to avoid hovering at one place for planning purposes.

2 Problem formulation

The proposed work is established with the goal of developing a rapid exploration algorithm to use MAVs as tools for exploration of unknown subterranean environments. The major challenge with MAVs is the limited flying time for autonomous missions. In this work exploration is considered as fixed time budget based missions to replicate the reality of the challenge in a subterranean exploration mission where the MAV is expected to explore for a given time budget and then autonomously return to base with the shortest yet safest path. In theory, the exploration part of the problem can be oriented as an exploration of bounded 3D space denoted as $V \subset \mathbb{R}^3$. The 3D space around the MAV is interpreted as three possibilities, a) occupied, b) free and c) unknown in order to utilize the sensor data for the MAV to perceive the environment around it. Occupancy probability based modelling is adapted in order to model free, occupied and unknown space around the MAV. In the theoretical aspect, the exploration will be considered complete when $V_{occupied} \cup V_{free} = V$ while $V_{unknown} = \emptyset$. $V_{occupied}$, V_{free} and $V_{unknown}$ represent the occupied, unknown and free space within V . The proposed REF framework is developed for its prominent use case in mines and cave environments where, MAVs could be used with the REF framework to rapidly explore and map unknown areas. Therefore, the theoretical exploration completion is evaluated based on fixed time budget based exploration missions where the MAV is deployed with pre defined exploration mission duration and once the clock exceeds mission duration, the MAV is required to follow a short yet safe path back to the base. The safe exploration of unknown and unstructured subterranean environments is subject to how well the MAV can navigate in previously unknown areas given bounds on actuation effort and safety risk margin in path planning. The safety risk margin m is defined such that in an expendable 3D grid based map (OctoMap) the path planning is constrained with $m * v_{res}$ margin from an occupied voxel while planning paths to a safe frontier. v_{res} is voxel resolution and therefore the risk aware path is in proportion to the grid resolution and risk margin. In order to be deployed

in a real scenario, the exploration and planning framework should adapt based on the available computational resources (processing power of the MAV to compute safe paths in grid based map). The limitation on planning safe yet fast paths is imposed in relation to how fast the MAV can plan the paths while utilizing minimum resources to efficiently explore the area. The performance evaluation of the proposed framework will be based on explored volume in fixed time budget based missions and distance travelled from the base.

2.1 Contributions

The exploration, global planning and navigation architecture of this work is part of the development efforts within the COSTAR team [1, 36] related to the DARPA Sub-T competition [11], while it is directly applicable for cave environments. Based on the above-mentioned state-of-the-art, the key contributions to this article are listed in the following manner.

- The main contribution of this work stems from the development of safe frontier points generation and local as well as global cost-based candidate frontier point selection method. In the presented work we extend the classical and rapid frontier exploration approaches with improvements concerning the safety of MAVs in the field as well as maintaining the agile nature of exploration. The proposed approach focuses on the local frontier selection that takes into account the position of such frontier relative to any static or dynamic obstacle in the field of view while also minimizing the yaw movement of MAV. When no such frontier exists in the local field of view, the global re-positioning of the MAV is triggered in order to lead the MAV to global frontiers that lead the MAV to more unexplored space. The global re-positioning approach is based on a cost function on the overall actuation effort (A cost that relates roll, pitch, yaw rate, and Thrust inputs to make a specific maneuver to move to a point) required by the MAV to navigate to a global frontier. The proposed global re-positioning of the MAV considers various factors such as MAV safety, actuation cost as well as how much of the unexplored space will be seen from a potential global frontier. Such contribution differentiates our method from other rapid frontier exploration approaches that directly switch to the classical frontier approach, instead in our method MAV globally re-positions itself based on multi-layer cost assignment in global frontier selection. As it will be presented, such contribution is particularly important in multi-branched tunneling or caving system exploration scenarios.
- The second contribution presented in this article is the integration of the overall autonomy framework which

addresses the problem of exploration, safety margin-based path planning, and reactive navigation through Nonlinear Model Predictive Control (nmPC) based control of MAVs. The dedicated risk-aware path planning and potential fields-based avoidance scheme incorporated within the proposed framework allows for pushing the limits of exploration in the candidate goal selection process in wide, narrow, and obstructed environments. Such integration allows realistic evaluation of the rapid exploration framework on large-scale maps. Simulations are performed for testing the proposed framework in multiple large-scale scenarios in order to benchmark the safety, speed, and versatility aspects of the autonomous MAV equipped with the REF approach.

The rest of the article is structured as follows. Section 2 presents the problem formulation considered in this work. Section 3 presents the proposed safe frontier points generation as well as intelligent goal selection with a focus on safe yet fast autonomous exploration addressing the minimizing actuation effort of the MAV. The section also describes the overall autonomy framework which is the combination of exploration, global path planning as well as nmPC based reactive navigation. In Section 4, a detailed analysis on simulation experiments is presented that proves the efficacy of the proposed scheme. Finally, Section 5 provides a discussion with concluding remarks on the proposed work.

3 Proposed approach

The proposed approach employs a frontier-based exploration technique which is modified with the focus on making exploration fast, safe, and versatile for a MAV with low computational resources and limited flying time. The proposed Rapid Exploration Framework is developed with the goal of planning the next exploration steps while navigating to the previously selected safe frontier goals. The low complexity of the algorithm for exploration is in line with the limited computational resource (processing power) available as onboard processors of MAVs. We use occupancy grid maps as a mapping framework, which can generate a 2D or 3D probabilistic map. A value of occupancy probability is assigned to each cell that represents a cell to be either free or occupied in the grid. In this work we are targeting 3D exploration of bounded and unbounded space therefore using the baseline framework of a 3D occupancy grid called OctoMap [22] we build on top of it in order to develop the proposed 3D occupancy checking framework used in this work. The expendable 3D occupancy grid-based mapper OctoMap uses a data structure in which each node has eight children nodes to represent the occupancy probability of 3D volume. This data structure

is referred to as *octree* from here on. Let us denote a voxel as $v(x, y, z)$. The voxel v is subdivided into eight smaller voxels until a minimum volume is reached. The minimum volume is the same as the octree resolution v_{res} . Based on the formulation discussed in [35] Corresponding to each sensor update if a certain volume in the octree is measured and if it is observed to be occupied, the node containing that particular voxel is marked as occupied. Using ray casting operation for the nodes between the occupied node and the origin (sensor), in the line of ray, can be initialized and marked as free. This process leaves the uninitialized nodes to be marked unknown until the next update in the octree. Let us denote the estimated value of the probability $P(N | z_{1:t})$ of the node N to be occupied for the sensor measurement (Point cloud data from a LiDAR or depth camera) $z_{1:t}$ by:

$$P(N|z_{1:t}) = [1 + \frac{1 - P(N|z_t)}{P(N|z_t)} \frac{1 - P(N|z_{1:t-1})}{P(N|z_{1:t-1})} \frac{P(n)}{1 - P(n)}]^{-1} \quad (1)$$

In Eq. 1, P_n is the prior probability of node N to be occupied. Let us denote the occupancy probability for node N to be occupied as P^o

$$v(x, y, z) = \begin{cases} Free, & \text{if } P^o < P_n \\ Occupied, & \text{if } P^o > P_n \end{cases}$$

Let us define the sensor range R and a sphere of radius r around the MAV. This radius r will be denoted as a cleaning radius from here after. Then after each update in the current octree, if a frontier lies inside this sphere, the frontier is marked as seen and the frontier is deleted from $\{F\}$. The cleaning radius is defined such that $r < R$ therefore new frontiers will always be generated at distance R and as the

MAV navigates towards the frontier, the frontiers lying within the sphere of radius r are deleted and less number of frontiers need to be iterated through in candidate goal selection process. The iterator is defined as it . The meanings of the important notations used in this work are presented in Table 2.

Algorithm 1 Safe Frontier Generation.

```

Input:  $v_{res}, Current\ octree, k, r$ 
Output:  $\{F\}, \{O\}$ 
1 for  $N : Current\ octree$  do
2   if  $P_N^o < P_n$  then
3     if  $N.distance() < r$  then
4        $it \leftarrow 0;$ 
5       for  $Neighbours : N.getNeighbour()$  do
6         if  $P_N^o > P_n$  then
7            $it \leftarrow 0;$ 
8           break;
9         else
10           $it \leftarrow it + 1$ 
11        if  $it \geq k$  then
12           $\{F\}.add(it\_N);$ 
13        else
14           $\{O\}.add(it\_N);$ 
15        for  $N : \{F\}$  do
16          if  $(N_{adj} + N_{m*vr_{es}}) \notin \{O\}$  then
17             $\{SF\}.add(N);$ 
    
```

The exploration framework presented in this work is a combination of three essential modules, namely the safe frontier point generator, the cost-based frontier point selection incorporating also collision check, and finally, the candidate goal publisher as presented in Fig. 5.

The proposed exploration strategy is subdivided into different modules which are comprised of individual components (octree generation, frontier extraction, Next Best Frontier goal selection, and planning to the goal) in order to establish information flow from raw sensor data to the planned path for the MAV to follow. The first module takes the Lidar point cloud as input and based on the occupancy probability formulation as mentioned earlier, converts the sensor measurement (point cloud ranges) in order to form an octree. The octree is defined as a tree data structure in which each sub-node is further divided into eight quadrants until the minimum volume is reached. The safe frontier point generator module generates all safe frontiers based on the octree where if a node N has at least k number of unknown neighbors then it is considered as a frontier as depicted in Algorithm 1. Let us define a risk margin parameter m related to the voxel grid resolution v_{res} . At any instance, in the exploration, if node N is currently checked for to be considered as a safe frontier then we also check the neighboring adjacent nodes defined as N_{adj} within the safety margin m .

In our approach, we formulate an additional layer of requirement in which we check the neighboring Voxels of

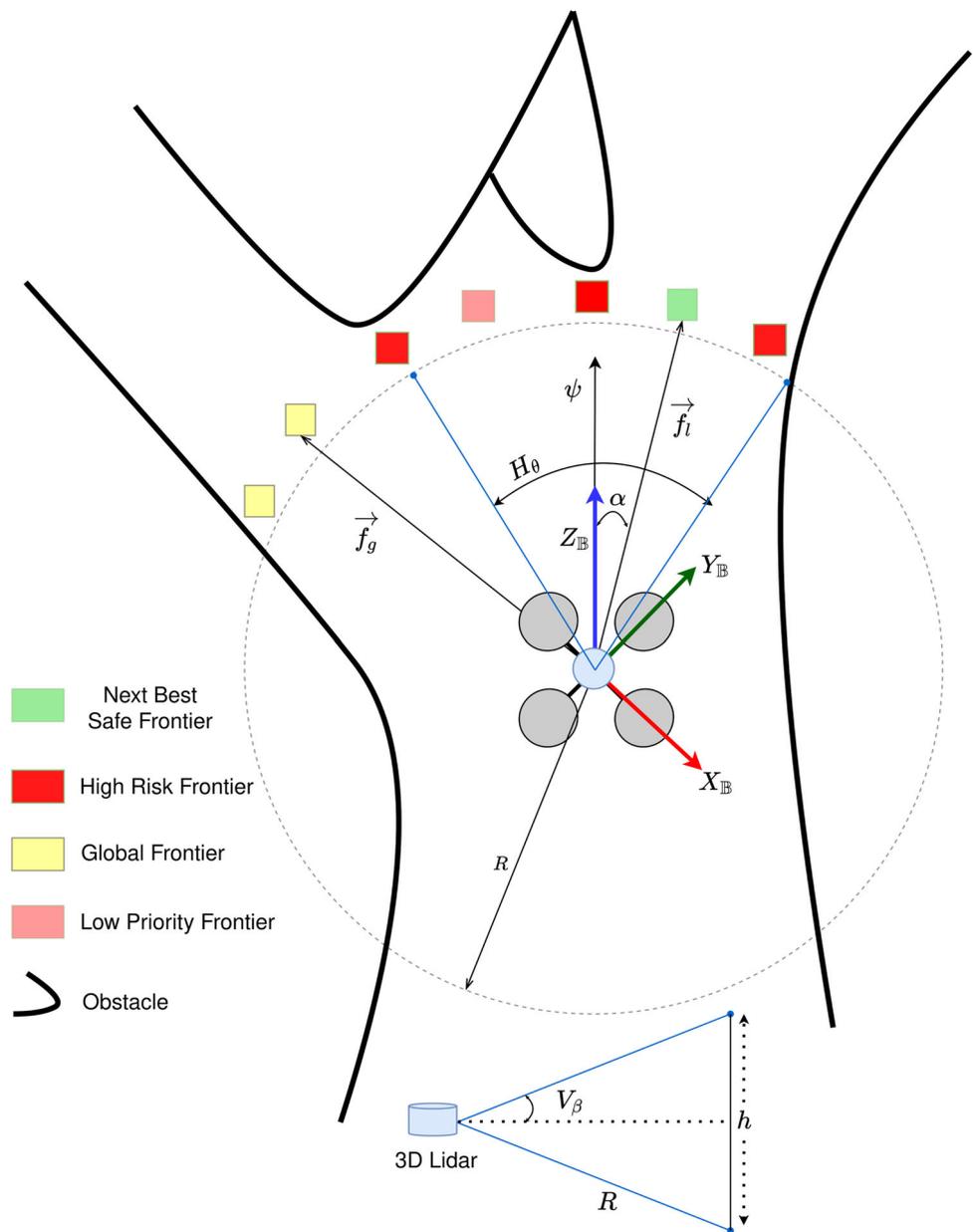
Table 2 Description of the notations used in proposed methodology

| Notation | Meaning |
|------------|--------------------------|
| $\{F\}$ | All frontier set |
| $\{O\}$ | Occupied nodes set |
| $\{C\}$ | Valid frontiers set |
| $\{SF\}$ | Safe frontiers set |
| $\{L\}$ | Local frontiers set |
| $\{G\}$ | Global frontiers set |
| R | Sensor measurement range |
| r | cleaning radius |
| m | risk margin |
| v_{res} | octree resolution |
| V_β | Horizontal FOV |
| V_β | Vertical FOV |
| $f(x,y,z)$ | Frontier position |
| $C(x,y,z)$ | MAV current position |

an uninitialized (Unknown) Node N as described earlier and $\forall(N_{adj} + m * v_{res})$ if $(P_{N_{adj}}^o \leq P_n)$ than the Node N is considered as a safe frontier node and is added to $\{SF\}$, where $\{SF\}$ is a set containing all safe frontiers. This means that a particular node N , its adjacent node N_{adj} as well as all nodes in the neighborhood of node N within the range of $m * v_{res}$ are checked and if all such nodes are seen to be free than the node N is considered to be a safe frontier. To be marked as a frontier, each node should have at least n number of minimum unknown or free adjacent nodes. This process makes a big difference in the computational complexity of the process because by specifying a certain risk margin m and minimum unknown or free neighbors k at the start of

exploration, the trade-off can be made between the number of iterations and coverage quality. Another improvement our approach presents is that by not allowing any frontier to be close enough to an occupied node in the context of risk margin, we guarantee that inaccessible frontiers can be eliminated which are generated due to the error in probabilistic occupancy mapping. The inaccessible frontiers are defined as the frontiers that are not safe to reach or impossible to reach in terms of MAV size and dynamics to pass through small openings in the map. This simply implies that the risk margin can be set in correspondence with the size of the MAV such that the inaccessible areas can be patched and modeled as occupied in the map. The parameters m as well as k are

Fig. 4 Frontier classification and notations used in the proposed framework



proposed with the focus of testing the proposed approach in extremely difficult areas such as caves and mines where the safety of the MAV is a major concern

Algorithm 2 Frontier Classification Based on Local or Global Exploration.

```

Input: {S $\mathcal{F}$ } k, r,  $\alpha$   $\theta$ 
Output: NBF, {L}, {G}
1 for N : {S $\mathcal{F}$ } do
2   if N.distance() < r then
3     it  $\leftarrow$  0;
4     for Neighbours : N.getNeighbour() do
5       if Neighbour.isOccupied() then
6         it  $\leftarrow$  0;
7         break;
8       else
9         it  $\leftarrow$  it + 1;
10    if it < k then
11      {S $\mathcal{F}$ }.remove(N);
12    else
13      {C}.add(it_N)
14    for N : {C} do
15      if ( $\alpha$  < ( $H_\theta$ )/2) & ( $\gamma$  <  $V_\beta$ ) then
16        {L}.add(it_N)
17      else
18        {G}.add(it_N)
19      if {L}  $\neq$   $\emptyset$  then
20        for N : {L} do
21          NBF  $\leftarrow$   $\arg \min_{\{N \in \{L\}\}} (\mathcal{E})_{local}$ 
22      if {L} =  $\emptyset$ , {G}  $\neq$   $\emptyset$  then
23        for N : {G} do
24          NBF  $\leftarrow$   $\arg \min_{\{N \in \{G\}\}} (\mathcal{E})_{global}$ 
25      if {L}  $\cup$  {G} =  $\emptyset$  then
26        it  $\leftarrow$  0;
27        break;
28        D $_x^*$ .ComputeHomingPath()
29        nMPC  $\leftarrow$  HomingPath
    
```

As defined in Algorithm 2, corresponding to each new sensor measurement we check if a $N \in \{F\}$ is still a frontier. We define a candidate frontier set denoted as $\{C\} \subset \{F\}$ which contains all the valid frontiers which will be examined based on the MAV’s position. A 3D Lidar is used in the proposed method to get sensor point cloud and thus, the framework generates frontiers in all directions surrounding the MAV but is limited in the vertical directions with the field of view V_β . In Algorithm 2, we classify the frontier nodes in two further sets $\{L\}$, $\{G\} \cup \{C\}$ named as Local and Global set respectively. Such Local and Global sets contain frontier nodes classified based on the selected horizontal and vertical field of view H_θ and V_β respectively as shown in Fig. 4.

This process allows us to prioritize the unknown space lying ahead of the MAV and if there exists no unknown space ahead of the MAV, the candidate goal is selected based on the global cost-based goal assignment.

$\forall f \in \{L\}$ are computed for extracting NBF such that $\alpha \in [-\pi, \pi]$ is minimum. The frontier points from occupancy formulations are generated in the world frame (\mathbb{W}) but the frontier vector \vec{f} is calculated relative to the MAV body frame (\mathbb{B}). As shown in Fig. 4, the angle α is calculated with respect to \mathbb{B} . If a frontier f and MAV’s current position in world frame \mathbb{W} is defined as $f(x, y, z)$ and $C(x, y, z)$ respectively then the angle α and γ with respect to body frame \mathbb{B} can be computed as,

$$\alpha = \tan^{-1}\left(\frac{f_y - C_y}{f_x - C_x}\right) - \psi \tag{2}$$

$$\gamma = \cos^{-1}\left(\frac{h}{2 * (f_z - C_z)}\right) \tag{3}$$

where ψ is the heading angle of the MAV and h is the vertical height of the footprint of the 3D LiDAR field of view.

As discussed previously the Algorithm 1 also outputs a list of occupied nodes $\{O\}$ which has occupancy probability P^o higher than 0.5 thus considering the cluster of occupied points lying in the field of view, the frontier nodes having a lesser avoidance cost are also favored to be the *NextBestFrontier*. The cost formulation for selecting a local or global candidate goal is as follows. If we define the current position of the MAV as $C(x, y, z)$ then the costs for local and global frontier selection can be formulated as,

$$(\zeta)_{local} = \frac{\overbrace{1}^{\text{Avoidance cost}}}{\underbrace{\mathbf{W}_o \sqrt{(p_x^f - p_x^{obs})^2 + (p_y^f - p_y^{obs})^2 + (p_z^f - p_z^{obs})^2}}_{\text{Heading cost}} + \underbrace{\mathbf{W}_h * \alpha}_{\text{Heading cost}}} \tag{4}$$

$$(\zeta)_{global} = \frac{\overbrace{\mathbf{W}_h * \alpha + \mathbf{W}_z * (f_z - C_z)}^{\text{Heading cost} \quad \text{Height difference cost}}}{\underbrace{\mathbf{W}_d \sqrt{(f_x - C_x)^2 + (f_y - C_y)^2 + (f_z - C_z)^2}}_{\text{Distance cost}}} \tag{5}$$

Where, \mathbf{W}_o , \mathbf{W}_h , \mathbf{W}_z and $\mathbf{W}_d \in \mathbb{R}$ are defined as weights associated to avoidance, heading, height difference, and distance cost respectively. We define the actuation effort \mathcal{E} as a function of cost such that

$$\mathcal{E} = f(\zeta + T_{hover})$$

where T_{hover} is the minimum thrust required for hovering with zero torques about the MAV arms. Thus, by optimally selecting the next pose reference command for the MAV the actuation effort can be minimized. The MAVs consume high energy to produce yaw torque due to the motor saturation constraints while also keeping the MAV hovering.

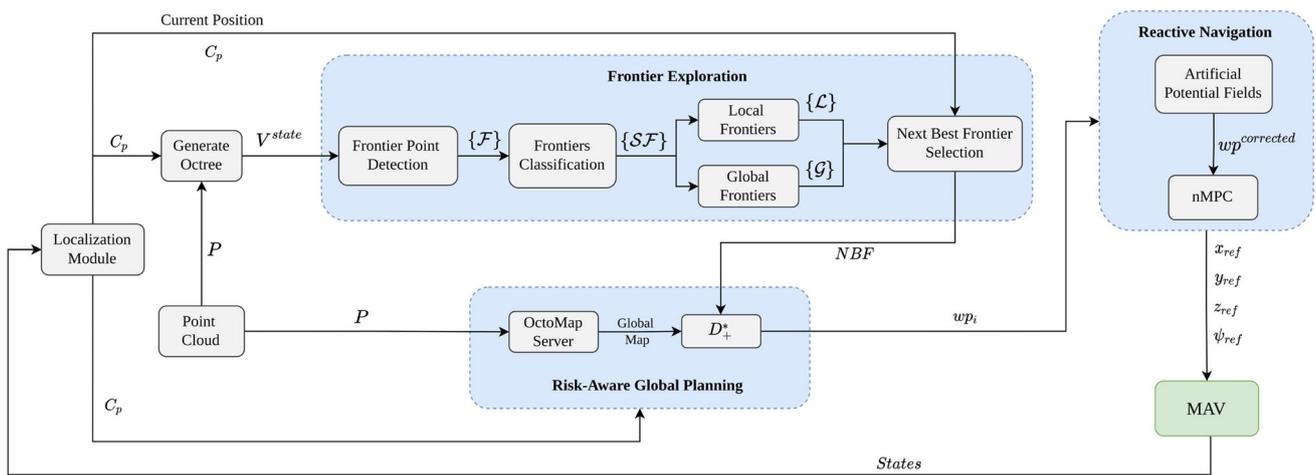


Fig. 5 The proposed overall autonomy and navigation scheme

The overall autonomy scheme of the proposed work is presented in Fig. 5. As discussed earlier, the framework uses 3D LiDAR or a camera depth cloud as point cloud input and upon point cloud filtering, the framework generates an octree of occupied, free and unknown nodes. Using the workflow described in Algorithm 1, the framework detects frontier points and classifies a set of safe frontiers. As presented in the autonomy and navigation scheme (Fig. 5), based on the local or global frontier, the risk-aware global planning module

plans a collision-free path to the next best frontier. The *NBF* is then fed into the reactive navigation and control framework to actuate the MAV to navigate to the selected frontier point. In Fig. 5 APF stands for Artificial Potential Fields that we have incorporated with Nonlinear Model Predictive Control for collision avoidance. The baseline framework for reactive navigation and control used in this framework is inspired by our previous work [29, 30]. The Next Best Frontier is sent to a risk-aware global planning module which is the exten-

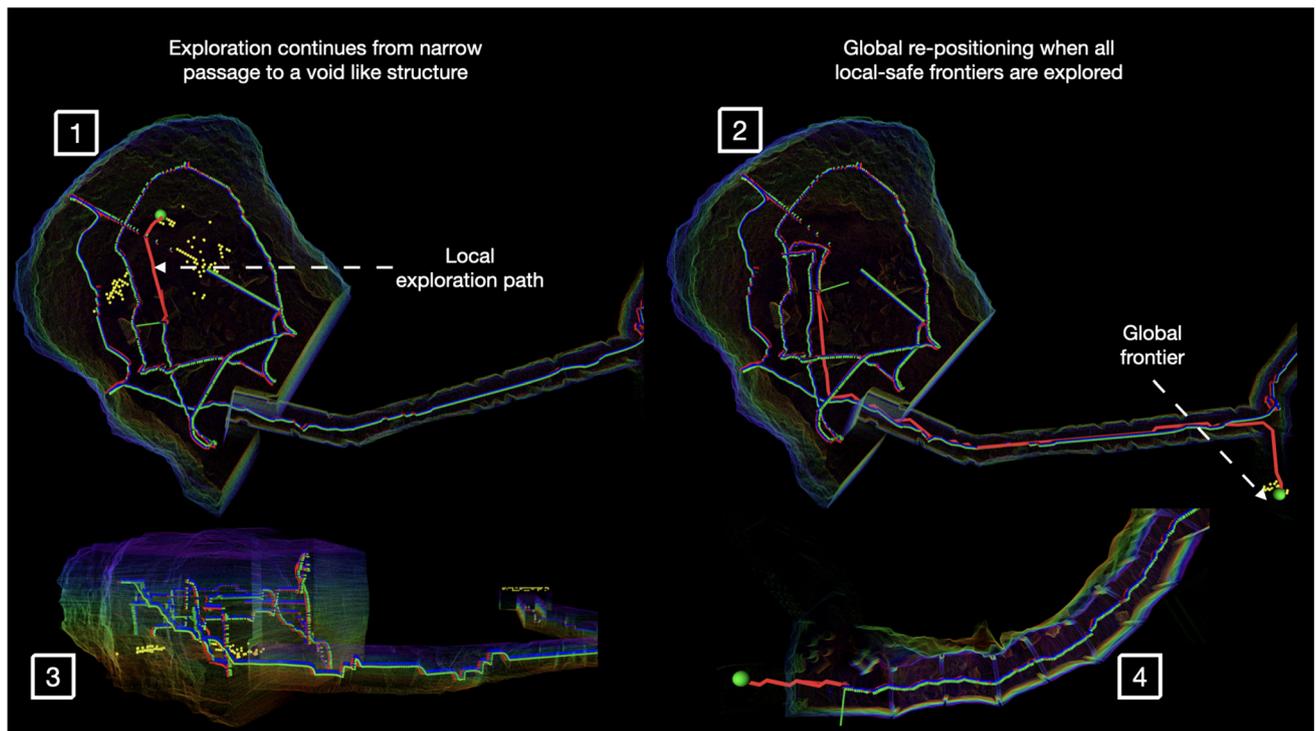


Fig. 6 DARPA-Sub-T virtual world: Exploration of narrow-confined passages as well as large cave-like voids using the proposed framework. In (1,2,3) the rapid exploration-coverage nature of the proposed framework is shown. In (4) the safe way-point selection and risk-aware planning to a safe frontier are shown

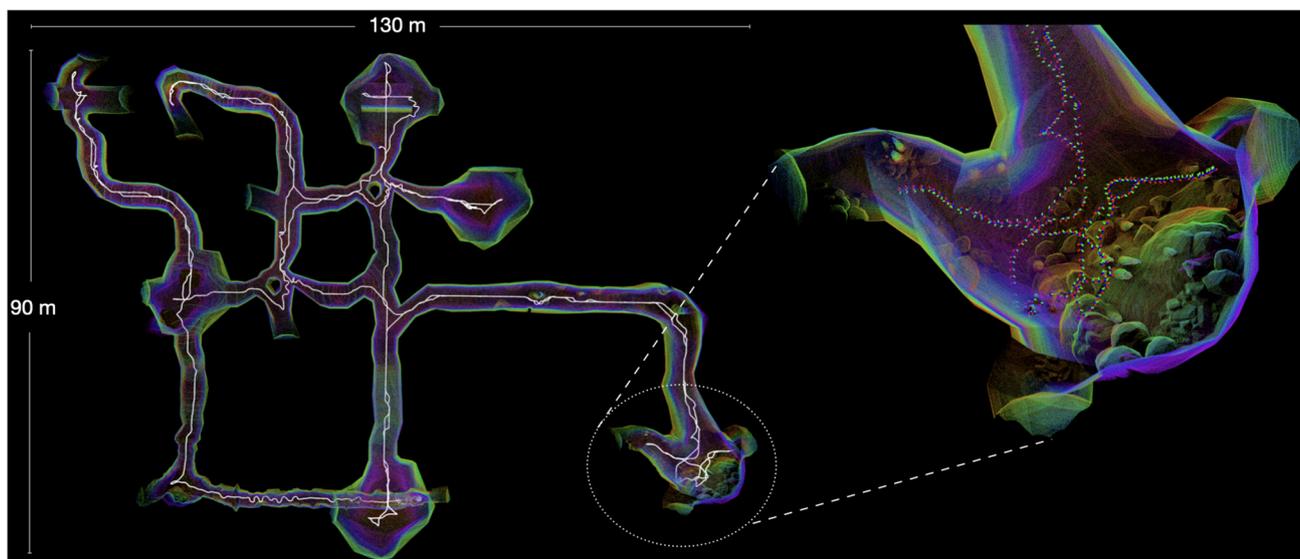


Fig. 7 Multi-branched large 3D virtual cave world exploration using proposed framework

sion of D^*Lite algorithm but implemented with an octomap framework in this case. The global planning module D^*_+ uses the modeled occupied space in order to plan a safe path to the NBF . The risk margin formulation in an expandable octomap grid for global planning is presented in detail in our previous work [25].

3.1 Supportive Autonomy Modules

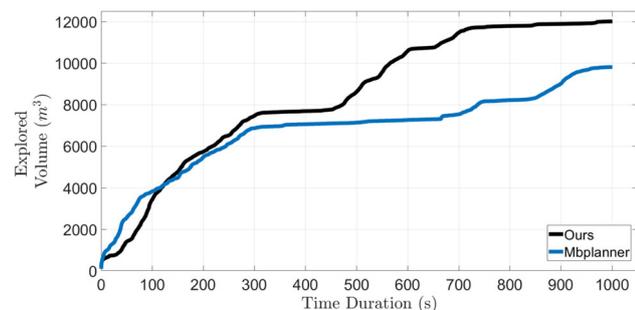


Fig. 8 Volumetric gain by the two methods

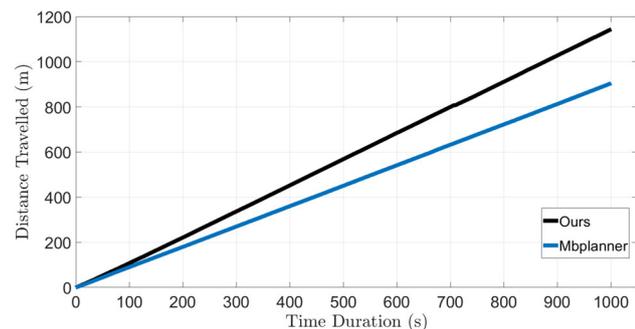


Fig. 9 Distance covered by the two methods

To enable the fully autonomous exploration mission, the REF is evaluated in conjunction with a set of supportive autonomy modules, seen in Fig. 5. The two core components are a fully reactive artificial potential field (APF), and a Nonlinear Model Predictive Controller (NMPC), presented in detail in the previous works [29, 30] that handles the local navigation after the next way-point is provided by REF. During the simulation evaluations, we assume that the estimated UAV state vector \hat{x} is provided by the simulator odometry, including position (p), velocity (v), and Euler angle states (θ, ϕ, ψ). To ensure no collision with the environment in case of a failure of the higher-level modules, we use an artificial potential field, that is directly using the raw LiDAR point cloud P . We use a repulsive force formulation similar to the legacy work in [51], but instead let each 3D LiDAR point closer than the specified radius of influence (or safety radius) r_s be summed to get the force total. This can be written as:

$$F_r = \sum_{i=1}^{N_{\rho_F}} L_r \left(1 - \frac{\|\rho_F^i\|}{r_s}\right)^2 \frac{-\rho_F^i}{\|\rho_F^i\|}, \tag{6}$$

where $\rho_F = [\rho_{Fx}, \rho_{Fy}, \rho_{Fz}]$ denotes LiDAR points relative to the body-frame of the UAV within r_s (e.g. points used for force calculations), and N_{ρ_F} denotes the number of such points. L_r is a repulsive gain that represents the largest possible repulsive force-per-point. The result is a fail-safe avoidance framework that does not rely on any object detection, segmentation, or occupancy mapping to maintain a safe distance from walls and obstacles. We also add saturation and rate-saturation on the repulsive force to prevent oscillating behavior. The attractive force F_a is simply the next way-point w_p provided by REF, that has been normalized in magnitude.

Table 3 Exploration volume and distance from multiple runs

| Mission Duration | Volume (REF) | Volume (Mbpplanner) | Distance (REF) | Distance (Mbpplanner) |
|------------------|--------------------|---------------------|----------------|-----------------------|
| 100 s | 3578 m^3 | 3840 m^3 | 163 m | 154 m |
| 300 s | 7854 m^3 | 6958 m^3 | 284 m | 236 m |
| 600 s | 11367 m^3 | 8438 m^3 | 670 m | 476 m |
| 900 s | 14477 m^3 | 9851 m^3 | 1066 m | 781 m |
| 1200 s | 17524 m^3 | 12760 m^3 | 1185 m | 962 m |

The APF works by shifting the position reference given to the control framework as $p_{ref} = F_a + F_r$. The controller is based on a previously published NMPC framework [31, 47] that takes the state vector $\hat{x} = [p, v, \theta, \phi, \psi]$ and full-state reference x_{ref} and generates optimal control inputs in the thrust, roll reference, pitch reference, and yaw rate commands as $u = [T, \theta_{ref}, \phi_{ref}, \dot{\psi}]$ to a low-level attitude controller, in this case, part of the RotorS framework, which very common cascaded control structure for UAVs. The NMPC problem is formulated as a minimization of quadratic costs on the states, inputs, and input rates (consecutive control inputs), with added constraints on the input magnitudes and input rates to enforce smooth and energy-efficient control behavior. To solve the resulting receding horizon optimization problem, we use the Optimization Engine [48], a fully open-source framework that provides very fast solutions for non-convex

nonlinear parametric optimization problems. We refer the reader to the previous works [29–31] for more details.

4 Exploration Mission Experiments

In order to validate and test the performance of our proposed exploration approach we use the M100 MAV provided in the open-source Rotors Simulator [20] framework. Next-Best-view [4] has been widely used for bench-marking the exploration-planning algorithms. In this work we compare our framework with the latest version of NBV, State-of-the-Art Motion Primitive Based planner (mbplanner) [12] which is developed also as part of the development efforts within DARPA Sub-T challenge. We use a custom cave model with multiple junctions, obstructed walls, narrow openings, and steep slopes as well as tunnels with dead-ends for simula-

Fig. 10 REF equipped MAV explores a large and wide virtual cave environment with different mission duration and octree resolutions

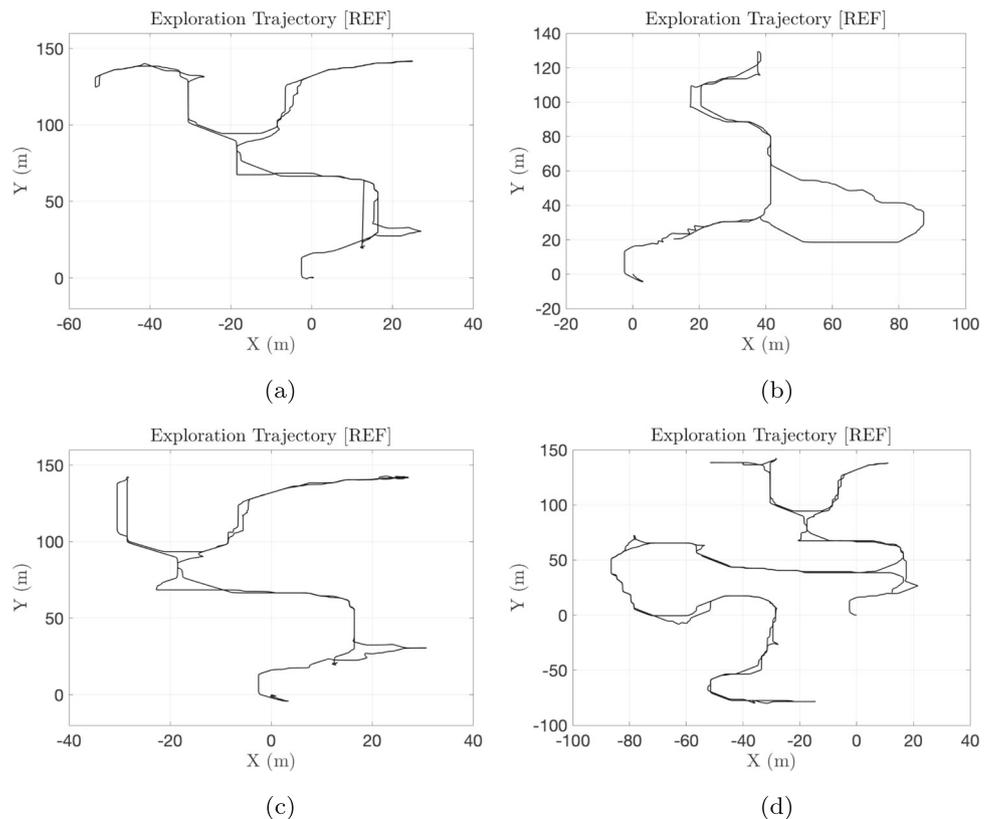
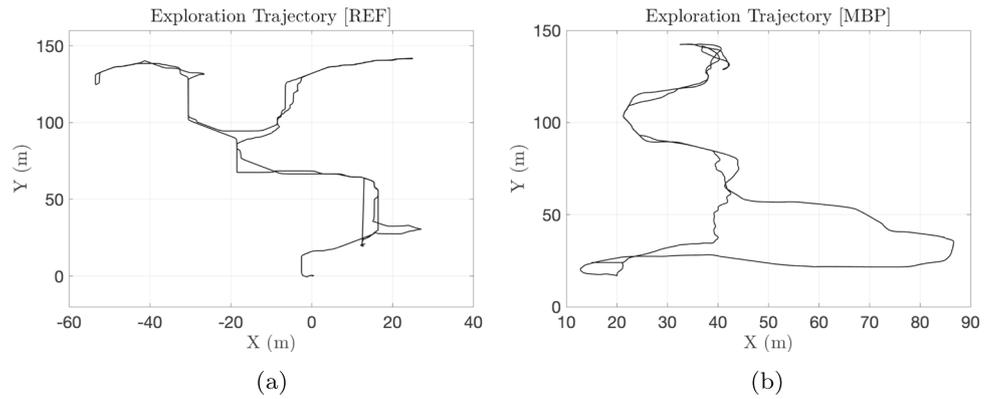


Fig. 11 400-sec mission: exploration trajectories, REF vs MB Planner. The proposed framework (REF) covers more ground in a given time while avoiding loops in one area due to the global re-positioning functionality



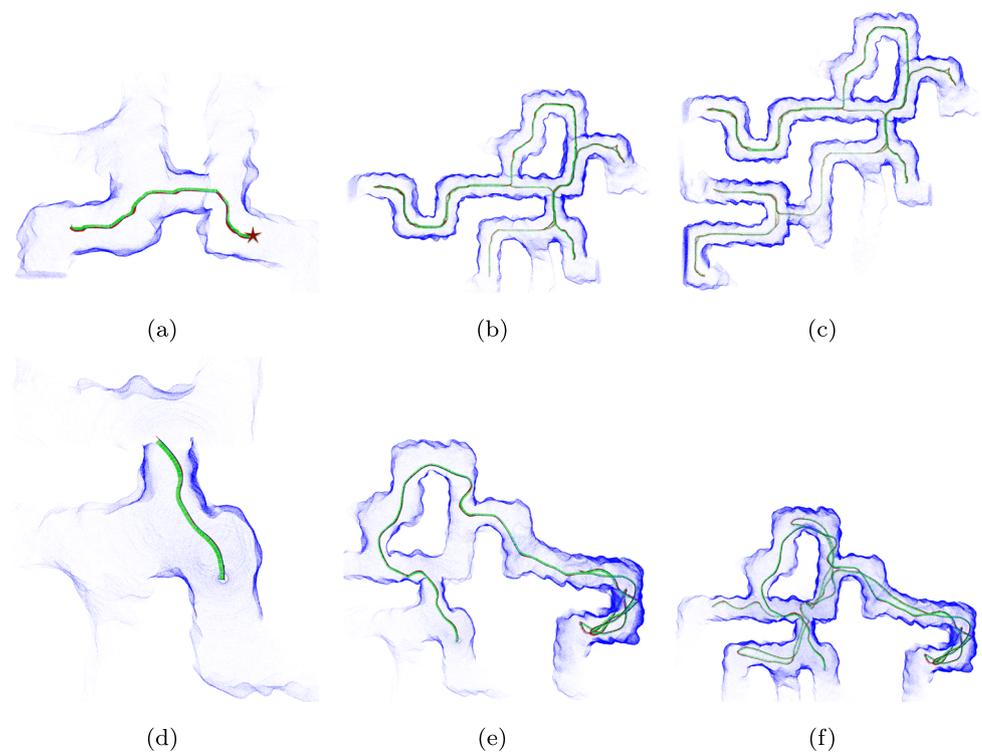
tion. The cave environment has been made open-source for the public [3]. For a fair comparison, all simulations are performed with the same computational unit having Intel core i7 processor and 16 GB memory on ROS Melodic running on Ubuntu 18.04. For mbplanner also the simulations are performed using the cave virtual world where the tuning of parameters such as MAV velocity, mapping resolution, and sampling time, was similar to the ones used for the proposed method.

In Fig. 6 different exploration instances are shown. As described in Section 3 the proposed framework (REF) also uses frontier cleaning radius and due to which coverage of large cave-like voids can also be performed while exploring. Using the proposed framework the MAV is also able to navigate in narrow and obstructed passages and at the

end of such passages if a void-like area can also be covered efficiently. The simulation experiment is also carried out to explore a multi-branched virtual cave environment having narrow passages continuing in different heights for a true 3D exploration. The environment is also made open source [27]. In Fig. 7 the exploration of the virtual cave environment is shown.

In Figs. 8 and 9 the explored volume and distance covered by the two exploration frameworks is presented. Figures 8 and 9 depict that our method performs significantly close to the State-of-the-Art mbplanner in terms of exploration volume of the cave environment and distance covered respectively. The proposed approach achieves a slightly higher explored volume for the same mission time, this is because of the novel Next Best Frontier selection approach as adapted in

Fig. 12 Time-based exploration: MAV trajectory (a) ours: 1 minute, (b) ours: 10 minute, (c) ours: 15 minutes, (d) mbplanner: 1 minute, (e) mbplanner: 10 minutes, (f) mbplanner: 20 minutes



Section 3. As presented in Fig. 12, the MAV trajectory in our approach is significantly in line with the goal of maximizing the movement into unknown areas while limiting repeated visits to already mapped areas. In Table 3 the exploration volume and distance traveled by the MAV in multiple different runs with different mission duration are presented for both planning frameworks. As it is evident from Table 3 that the proposed Rapid Exploration Framework (REF) shows higher exploration volume as well as ground covered by the MAV in multiple different runs because of the nature of computing next paths while navigating to the current path. The higher exploration volume and distance are highlighted in bold to signify the gist of the comparison. All missions considered in Table 3 have the same start positions for both planning frameworks and the MAVs do not return to base in considered cases, therefore, showing the exploration capability comparison in the given time with the same configuration.

However, it is also important to mention that even though the $V_{unknown}$ sampling approach in both methods is different, the next way-points in both cases are selected with the focus on maximizing the information gain and exploration volume at the same time.

In Fig. 11 the exploration mission trajectories are shown for REF and mbplanner with the same mission duration (400 s). In Fig. 11 it is evident that the MAV covers more ground in a given time using the proposed framework.

In Fig. 12 in both methods, the overlap in trajectory is seen. This overlap is mainly due to the lower information gain (corresponding to mbplanner) and $\{\mathcal{L}\} = \emptyset$ (corresponding to our approach) resulting in the MAV changing direction and moving to other unexplored areas. In Fig. 12c it is evident that using the proposed global frontier selection strategy, the $NBF \in \{\mathcal{G}\}$ is selected such that the overlap in trajectory is minimal. In Fig. 10, the MAV trajectory is tracked in XY while exploring the lava tube virtual environment. The tracked trajectory is presented for visualizing the *Look-Ahead-Move-Forward* nature of the proposed exploration framework. Due to such nature of exploration, the proposed framework is able to efficiently map new areas within the given time and thus efficiently utilize the resource-constrained MAV's flight time. In Figs. 11a, b and 10c a 400-second exploration mission is performed with different voxel resolutions. In Figs. 11a, b and 10c the exploration is performed with voxel resolution 0.3, 0.5, and 0.7 m respectively. It is evident that corresponding to each voxel resolution in the exploration mission, the MAV takes a different path while exploring based on the selected NBF in each iteration. All exploration missions are performed with the maximum forward velocity of the MAV as 1.5 m/s. In order to map the same environment even more quickly, an exploration mission with a voxel resolution of 0.9 m and mission duration of 900 seconds is performed and the tracked trajectory of the MAV is presented in Fig. 10d.

5 Conclusions

In this article, we proposed a Rapid Exploration Framework for deploying autonomous MAVs in unknown areas such as caves and mines. We present a novel candidate goal selection method with the focus of minimizing the actuation effort of the MAV by employing the Look Forward Move Ahead approach. We compare the exploration scenario in the same environment with the motion primitive-based planner which is a remarkable extension of the Next Best View approach. In terms of volumetric gain and distance traveled, we achieved similar results to that of the mbplanner. We also address the trajectory overlap issue by introducing a simple yet efficient cost-based goal selection approach that prevents the MAV from Unnecessarily traveling to previously visited areas while also keeping the look forward move ahead approach as a priority. As future development efforts, we plan to conduct some field experiments to explore abandoned mines and underground cave structures.

Author Contributions Akash Patel: Development, implementation, and system integration, relating to all presented sub-modules and developments, main manuscript contributors. Björn Lindqvist: Control and obstacle avoidance modules advisory. Christoforos Kanelakis: Software integration and high-level advisory. Ali-Akbar Agha-Mohammadi: Advisory, development lead for Team CoSTAR in DARPA Sub-T Challenge. George Nikolakopoulos: Advisory, manuscript contributions, head of the Luleå University of Technology Robotics & AI Team. All authors have read and approved the manuscript.

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Declarations

Ethics Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish All authors comply with the consent to publish.

Conflict of Interest The authors have no conflicts of interest with any related parties.

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