Literature Study

Multi-drone Active Perception with Human-guidance

Nikhil Sethi [1] [†]

MSc. Robotics, Technische Universiteit Delft

February 2024

Submitted to

Daily Supervisor: Max Lodel, PhD Student [†]

Primary Supervisor: Javier Alonso-Mora, Associate Professor [†]

[1] n.sethi@student.tudelft.nl

[†] Department of Cognitive Robotics, Technische Universiteit Delft

Contents

Chapter 1

Introduction

Public safety and security stand at the forefront of societal concerns, requiring effective and responsive measures to address various challenges like disaster management, law enforcement, firefighting, and monitoring.

Traditionally, human involvement in frontline tasks has raised numerous concerns. For instance, mine rescues under harsh conditions pose health risks, including a high potential for heart-related illnesses [4]. Responders to earthquakes and nuclear disasters face not only physical harm but also mental trauma from disturbing conditions like gore and unpleasant smell [3]. Organised crime and law enforcement can incur significant economic costs and leave lasting social implications for victims, offenders, and society at large [1]. Such challenges, coupled with subpar compensation, raise ethical questions about labor practices. The complex interplay of health risks, ethical considerations, economic burdens, and societal consequences underscores the need to reevaluate our approach to these demanding tasks.

The integration of robotic systems presents a promising avenue for efficient, safe, and ethical solutions to such challenges. Noticeably, emergency response tasks involve exploring unseen environments, gathering information about relevant objects, and reaching inaccessible areas – tasks that robots are good at. Moreover, robots are cheap and expendable when compared to the cost of human lives. Conversely, humans are great at situational awareness, contextualizing gathered information, and adapting to unpredictable scenarios. This duality motivates the central focus of this literature review: *harnessing human-robot teams to look for objects of interest in unfamiliar environments.*

1.1 Problem domain

Naturally, the central topic branches into distinct sub-domains within robotics (highlighted bold). Successfully uncovering interesting objects requires a sophisticated **perception** pipeline that not only generates rich 3D information about the environment but is also capable of **semantic** scene understanding. The importance of objects in a scene can be predetermined or dynamically learned through **human-in-the-loop interventions**.

But understanding object priorities and localising them using passive percepts is only part of the problem. In **real life scenarios** like search and rescue, planetary exploration, disaster response etc., gathering information and updating the context dynamically is crucial and requires **active perception**. This need for mobility in cluttered environments calls for agile aerial robots like **drones**, that can venture into dangerous territories and provide unparalleled situational awareness. Such a framework requires a tight coupling between **planning**, **control** and perception, similar to how humans reason in cluttered environments.

Furthermore, real-time tasks such as **exploration** are inherently time-sensitive, and they can benefit from **workload** distribution among multiple coordinating robots which also makes methods like **multi-robot coordination** worth considering.

These are inherently hard problems because of several reasons:

- Partial Observability: Any exploration task in an unknown environment constrains the agent to plan only with respect to what it sees (or has seen). For instance, when using a depth camera on a drone the sensor range might not pickup obstacles and targets that lie in unseen areas. How do we plan to find a target we can't even see? Such situations require reasoning under uncertainty and effectively integrating planning and perception as a joint task which is a highly nonlinear problem.

- Challenging environments: The environmental situations relevant to this study impose high demands on the responding agents, making the problem multi-modal. For example, in a SAR scenario, the environment is usually unmapped and unstructured, necessitating enhanced sensing capabilities. Additionaly, the critical balance of minimizing time to search and maximizing information gain complicates the planning problem. Moreover, these problems need to be solved in real-time within the hardware constraints of the robot. Often, only a subset of these problems are solved at a time which makes it hard to actually deploy these systems when they are needed most.

- Contextual priorities: The importance of an object in an environment is highly context dependent and requires information about not only the current environment but past experiences as well. Humans are notoriously good at tasks like this. For instance, in a search and rescue situation, first responders would give more importance to dynamically moving, human shaped objects, but in a counter narcotics situation, storage objects like bags, containers, shelves would attract more attention. This can be seen as a function that maps current percept to priorities. Implementing such a generalised function that can capture human experience is non-trivial and approximate techniques are often used.

- Practical aspects: One of the main goals of this study and the eventual thesis, is to deploy the algorithms on a real system with computational budgets and sensor constraints. Within these constraints, the set of algorithms become limited and the assumptions on the environment have to be relaxed. An interesting aspect which makes it even harder is that for first responders on the frontline, it matters greatly that a robotic system is reliable and explainable. As this study will explore, this also makes it difficult to incorporate learning based techniques, and drives more attention toward optimization based and combinatorial methods.

1.2 Research Questions and Topics

The problem domain is further refined by dividing it into islands of research based on two ideas:

- The way these islands are constructed in academia. For example, researchers who focus on active perception also focus on semantics and exploration so they can be grouped together.
- A logically layered separation of ideas that builds up in overall system complexity (single robot → multiple robots → human-robot teams). Each of the islands have their own research question that is explored in it's respective chapter.

To ease understanding for the reader, the references for each cluster are separated chapter-wise and the three topics are labelled with their initial letter for citations. For example [A4] refers to the 4^{th} reference from the **A**ctive perception chapter. A common theme throughout all the topics/questions is their ability to be deployed on real systems and hardware.

Active perception and exploration (A)

The first cluster looks at the problem from a single agent's perspective. Active perception is the task of using motion to gain more information about the environment and increase the quality of the perception task [A4]. In other words, planning to see better and seeing to plan better. Active perception is a general framework for a variety of tasks like surface reconstruction [A45], monitoring [6], exploration etc. In this study, the scope will be limited to target search and exploration of cluttered unknown environments using a quadrotor MAV as the robot platform. An important consideration is to choose methods that display robust real-world experiments in challenging environments. These choices for refinement are motivated in chapter 2. The research question then is formulated as:

What are the state-of-the-art planning methods and baseline techniques for target search and volumetric exploration using Micro Aerial Vehicles (MAVs)?

Multi robot coordination (M)

The second broad cluster increases the complexity and deals with forming robot-robot teams. In tasks like exploration, where looking for objects of interest rely on acquiring a lot of information quickly, there can be a clear advantage to using multiple agents. Moreover, when combined with active perception multiple robots can help resolve uncertainty by providing concurrent spatial viewpoints of the entire scene – a task that a single agent would do in the temporal dimension [A4]. Challenges for multi robot active perception can range in both perception and planning domains. In this research, the scope is limited to only planning methods and algorithms. It will therefore be assumed that multiple robots can localize themselves and establish a common frame of reference via state of the art techniques like [M25]. The challenge here is to coordinate and plan motions of the robots such that information is gathered effectively.

What methods exist in literature for coordinating the actions of multiple robots engaged in target exploration in an unstructured cluttered environment?

Humans-in-the-loop (H)

The third cluster adds yet another layer of complexity and explores human-robot teams. The key motivation behind this section is that humans are really good at assessing situational awareness based on the current, past and future context. It is assumed here that encoding this experience into a large parameterised function is non trivial. Hence, shared autonomy solutions are preferred in which humans collaborate with robots, each performing what they do best. In the context of human robot teams, collaboration can take many forms including shared control [H12], tele-operation [H21], guided exploration [H4]. The challenges is to determine the stage at which the human must be incorporated in the entire system, ensuring low cognitive workload and maintaining situational awareness while guiding search towards objects of interest.

How and when should a human be included in a multi-robot system for enhancing the quality of the target search task?

1.3 Metrics

To assess and compare works in general, metrics like the publication quality, journal and lab reputation, citations, and open-source code were used. Among each research cluster however, some metrics specific to the goals of this study and thesis were also defined.

- Real-world implementation details: In the context of this study, greater weight is assigned to research papers that offer working implementations. A common trend in robotics research is to only test results in simulation environments that don't transfer well. Factors such as computation budgets, sensor noise, and real-world constraints greatly influence algorithm choices and environment representations. The importance of explainability and reliability underscores our preference for research that provides practical, hardware-oriented solutions over theoretical formalism, though an ideal combination of both is acknowledged.

- Testing: Situations like SAR and exploration often have extreme environments and testing algorithms in a diverse set of simulation scenarios is integral for good sim-to-real transfer. Therefore, more importance is given to works that can demonstrate testing and benchmarking in such environments.

- Task relevance: Finally, it is crucial to seek out papers that actually address the specific task at hand. For instance, in the case of human-in-the-loop interventions, methods that allow such interactions are preferred. In contrast to the prevailing 'end-to-end' solution mindset, hierarchical discrete approaches are favored. This choice is motivated by the hypothesis that it simplifies the integration of human interventions and multiple robots into the overall system, and keeps reliability high, which is a priority in public safety scenarios.

1.4 Structure

The three individual clusters are explored chapters 2 - 4 and links are drawn between them as the complexity increases. Each chapter's introduction starts with a motivation for the study and a brief review methodology which includes keywords to reproduce the work and overall comments about the searched papers. While each chapter provides detailed sub-conclusions, chapter 5 serves as a combined summary, answering the research questions from section 1.2. A knowledge graph is created to facilitate the reader's understanding of the key topics explored (fig. 5.1). Finally, section 5.2 outlines the proposed approach for the thesis, including a research statement and the problem formulation. The proposed plan culminates in a tentative timeline. By the end of this study, the author aims to draw conclusions from the breadth of work, formulate specific research questions and identify a few key works that can be used as a baseline for potential contributions.

References

[1] Sam Brand and Richard Price. The economic and social costs of crime. 2000.

[2] D Calisi, A Farinelli, L Iocchi, and D Nardi. Autonomous exploration for search and rescue robots. *WIT Transactions on the Built Environment*, 94, 2007.

[3] Angela Davids. Urban search and rescue robots: from tragedy to technology. *IEEE Intelligent systems*, 17(2):81–83, 2002.

[4] Glen P Kenny, Jill Stapleton, Aaron Lynn, Konrad Binder, Cheryl Allen, and Stephen G Hardcastle. Heat stress in canadian deep mechanized mines: Laboratory simulation of typical mining tasks performed in varying environments. In *Proceedings of the 13th International Conference on Environmental Ergonomics, Boston, USA*, pages 441–445, 2009.

[5] Jochen Kleinschmidt and Luca Trenta. Scanning the horizon: Drones and counter-narcotics in latin america. 2022.

[6] Mitchell B Lyons, Kate J Brandis, Nicholas J Murray, John H Wilshire, Justin A McCann, Richard T Kingsford, and Corey T Callaghan. Monitoring large and complex wildlife aggregations with drones. *Methods in Ecology and Evolution*, 10(7):1024–1035, 2019.

Chapter 2

Active Perception

The idea that perception and action are closely coupled is not new. One of the most early studies is Gibson's seminal work on the theory of ecological optics and links of perception with motion [A24]. He supported the view that perception is not just passive sensing but active information retrieval from the environment [A14]. In [A24] he states that the environment offers *information* and *affordances* to the agent by virtue of it's optical structure. The agent can then selectively attend to relevant information perform "a set of transformations" via motion to perform exploration and build "a cognitive map of the environment". For a comprehensive overview of the costs and trade-offs associated with active vs. passive perception the author recommends a read of [A52]. This paper also puts active perception into the broader concept of attentional mechanisms that humans use for visual cues.

Gibson's work inspired the field of active perception and it's extension to fields like robotics. An early [A1] and revisited [A2] account of this field by Bajcsy et. al. gives a more system level view by formalizing active vision as an intelligent data acquisition and control problem which is helpful in a robotics context. In the first paper, the authors classify various kinds of active perception. For this study and research, the control of several views (Level 5), and semantic interpretation (Level 6) will be considered. The second paper classifies active perception on a functional level (as opposed to a systems level) by explaining the Why, What, Where, How and When of the task. For instance, semantic object guidance can address *What* to object focus on, and attention mechanisms combined with frontiers (section 2.1) can address *Where* and *When* to look for an object.

Review Methodology

In the context of this study and thesis, the active perception topic is considered the core problem and human guidance and multi robot systems are built around this framework. Consequently, this chapter is covered in greater depth with more papers and fundamental concepts. Target search is considered as a separate topic from exploration because there exist fundamental differences that can change the approach and performance statistics. **Keywords**: Robot exploration, active perception for drones, frontier-based methods, viewpoint sampling, semantic relationships for visual search, target navigation, combinatorial planning, visual attention, search and rescue.

2.1 Exploration

Exploration is a fundamental component for deploying robots in domains such search and rescue (SAR) [2], wildlife monitoring [6], and counter narcotics [5]. Unlike earlier methods where mapping precedes navigation, exploration focuses on planning under partial observation and dynamically uncovering new regions of the area in an efficient manner. This partial observation constraint and the uncertainty of cluttered environments makes exploration a hard problem to solve and there are dedicated challenges in the research community solving specific problems [M21]. In this section the key technical elements for exploration are explored, the primary one being active perception. Note that there is a lot of overlap in exploration using single robots and multiple robots. In this section, only the former is explored because chapter 3 is dedicated to multi-robot coordination. Exploration is commonly achieved using two broad fields: frontier based, and sampling based methods.

Frontier based methods

First introduced in [A57], frontiers are defined as boundaries between known and unknown space. They are detected and updated as the robot moves and senses more of the environment. While the original paper uses simple depth-first search, there have been many extensions like [A31] where reachability maps which can be recursively queried to reach the closest frontier with the shortest path. In [A12], the authors bias selection based on flight direction resulting in faster speeds and conclude that such approaches work best in structured office like environments but don't provide added benefit in cluttered environments where there are significant corners and turns. In [A43], deep reinforcement learning is used to choose the appropriate frontier as opposed to geometric information based strategies. But using learning based methods for SAR is often limited by the ability to gather sufficient training data [M21], and less reliability.

The key for the proliferation of frontier based methods is that they are direct discrete representations of the environment. Such discrete maps are practical because they can be stored efficiently [A32], and with image-processing techniques like convolutions it makes it easier to compute functions over these maps. This allows the frontier based methods to be deployed readily on real systems which is also critical from this study's point of view. However, these methods assume that all frontiers carry equally important information and just navigating to them will eventually lead to exploration [A12]. This might be a reasonable assumption when the scenario is simple and needs to be completely mapped with a certain accuracy. However, in situations like target exploration where certain regions may be more important than others, sampling based techniques which can directly evaluate the information gain at viewpoints might be preferred.

Sampling based methods

A number of works use a utility function to directly evaluate the cost of looking at a region of space with a 'viewpoint' without relying on structures like frontiers [A25]. These methods are broadly characterised as sampling methods because multiple viewpoints are sampled in free space. The utility function can be the amount of unknown volume seen from the view or information based metrics like entropy. These approaches are closely linked to the Next Best View (NBV) strategy which was initially developed for multiple view surface construction, a classic active perception task [A13]. Simple approaches like [A51] extend the frontier concept by clustering frontiers and using their centroids as views. The view can then be selected based on the number of unmapped cells and cost-to-go [A25]. A common approach is to pair such methods with probabilistic path planning algorithms like Rapidly Exploring Random trees (RRT). In [A5], a tree is expanded and evaluated with nodes as viewpoints, and the first edge leading to the best viewpoint is executed. This tree is computed at each iteration and the branch is selected in a receding horizon fashion. The paper provides computational complexities of each step as well. An interesting inference from the paper is that when a robot comes across views that have been previously explored, the upper limit of N_{max} nodes is easily surpassed, necessitating the addition of numerous nodes to the graph in order to identify a viewpoint that can offer at least some information gain ($g_{best} > 0$). This increases the computational requirement for large trees in big open spaces which is a limitation of sampling based methods [A12]. The authors in [A19] address this limitation and further develop a graph based planner which is more suitable for narrow spaces like caves. A state-of-the art work in [A7] does planning in two stages. A coarse global path connects sub-spaces in the environment and within these sub-spaces, viewpoints are sampled intelligently to observe surfaces. A travelling salesman problem (TSP) is solved across the viewpoints and sub-spaces to connect local and global plans. The algorithm also has a multi robot version which is discussed in chapter 3.

Combined approaches

The above two sections show that hybrid approaches are the way to go. Frontiers can be used to detect global regions of unknown space, and viewpoint sampling can be used to carry out refined myopic perception. A schematic diagram (Fig. 2.1) places the pipeline in the context of active perception. This combined pipeline is becoming increasingly common in literature [A16] [A41] [A49] [A60]. Viewpoints can evaluate the gain directly from frontiers using utility functions like information gain [A41] or mutual information [A11]. In [A60] the utility function is simply defined as the number of unknown voxels, which is considered to be sufficient. The research in [A49] introduces several computational improvements compared to [A5], including caching potential information gains and performing sparse ray casting. This approach is further expanded in [A16], where the optimization balances information gain with the drone's dynamics to achieve faster exploration. However, the viewpoints are not systematically visited and RRT based approaches can be considered greedy, as discussed in [A7]. Recent state of the art works like [A7] and [A60] address this by solving a TSP over candidate viewpoints, although information gain is not considered in the objective. In contrast, the method in [A33] uses a 2-opt heuristic for the TSP which simultaneously considers distance, coverage efficiency and information gain. This enables planning of more efficient paths and reduced repetition. This method could potentially be employed to prioritize viewpoints based on the importance of different objects in the environment. However, it is worth noting that the study's experimental evaluation is lacking, and a ground robot is used instead of an aerial robot.

Some approaches model the space as a Partially Observable Markov Decision Process [A37] [A6], but they are limited to low dimensional observations (2D maps) and action spaces (ground robots). In [A37] the authors use a global heuristic like prior information or frontiers to deal with the low horizon limitations of a POMDP. In [A6] and [A4] the authors use Monte Carlo Tree Search (MCTS) to expand trees to search for high reward regions, similar to [A53], where an RRT is expanded to detect frontiers. However, the results are limited to simulation.

Another set of approaches explore learning based techniques like reinforcement learning for partial tasks like information gain calculation, as seen in [A42] and [A44]. Alternatively, some approaches follow the end-to-end paradigm where raw sensor data is processed to directly generate control commands via neural networks. However, a consistent theme across the examined literature is that the results are often limited to simulation [A20], confined to grid worlds [A27], or involve simplified experiments in well defined structured environments [A50] [A15]. In particular, end-to-end approaches currenlty struggle with generalisation to real settings. Black-box planning and control methods also tend to keep the human operator out of the loop which might be undesirable in emergency response scenarios. Despite these limitations, partial learning approaches do have potential when developed appropriately. A recent state-of-the-art work in [A42] uses neural networks to do collision avoidance and plan visually attentive paths in perceptually degraded environments. The experiments in this work are highly sophisticated and are a good reference for future work.

A common trend was observed in the papers accumulated: Discrete methods like volumetric grids and combinatorial optimization are simpler and practical to deploy on real hardware. Moreover, they scale better with an expanding space, and are more reliable than stochastic ones (RL, MCTS) because decision-making is reproducible. These features also make it easier for a human to work alongside the system in semi-autonomous fashion and provide task-relevant interventions. Section 2.3 summarises the conclusions for the exploration section.

2.2 Target search

Apart from exploring and mapping the complete environment, humanitarian scenarios like SAR require searching for specific objects that are more relevant than others. These objects can be known a-priori, or they can be discovered incrementally as the context for the situation builds. For example, in an earthquake, the search for a victim could

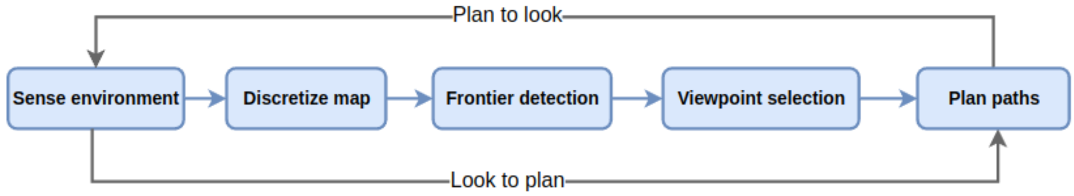

Figure 2.1: Active perception pipeline

start by exploring areas such as the living room, then progressing to identify objects like tables, and ultimately locating humans who might be trapped underneath.

This problem is called target directed exploration or path planning for relevant areas. Papers on inspection, coverage path planning, and object mapping are also included but with a weak comparison. The scope of this study focuses on uncovering *static* objects of interest quickly rather than ascertaining their fine grained nature which is an inspection task. Fields like visual attention and semantic segmentation are relevant to study target exploration tasks.

Visual Attention

Visual attention is defined as the selective gating of visual information in percepts [A54]. It is classified into two types. *Bottom-up* attention refers to an object's intrinsic drive to attract attention, often called saliency. This includes features like brightness, colour, texture etc. *Top-down* attention involves the agent's deliberate decision to focus on specific objects guided by prior knowledge and experience. For instance, a human searching for keys in a room even though they are not salient (Fig. 2.2). The figure also shows the importance of situational context and how both bottom-up and top-down attention are relevant for humans [A35].

The work in [A18] extends [A5], and actively looks for 'salient' objects in the environment to plans viewpoint trees with a modified exploration gain. The authors in [A8] also explore a similar idea by using particle distributions which indirectly represent attentive regions in space and help the robot navigate. But like the authors in [A5] explain – "the saliency is independent of the nature of the task ... can be considered intrinsic motivation for the robot". Contrarily, in this study, we want *explicit* motivations (top-down attention) to be set for objects relevant to the task and situational context. In [A22], a top down approach is used to rank potential objects of interest using a 'bag-of-features'. This ranking formulation could be particularly useful from a human intervention perspective. Perhaps a combination of both approaches, where a target exploration robot prefers salient objects while exploring but it can switch to a top-down context when encountering an object of interest is required. Such an approach has particularly been found to be useful in cluttered search and rescue environments [A47]. The paper is also

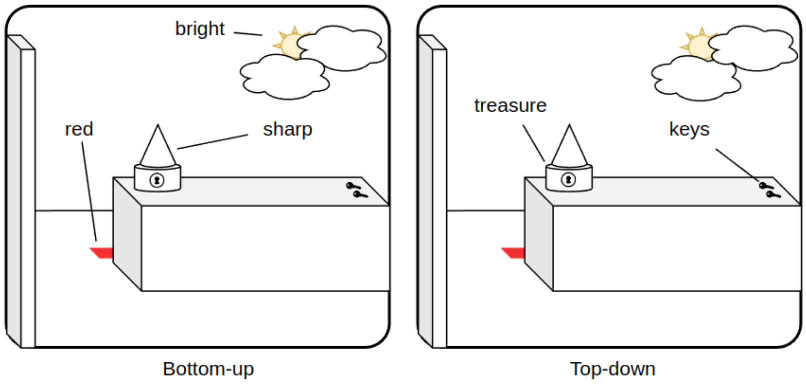

Figure 2.2: Bottom-up (left) vs. Top-down (right) attention. It might be worth looking at salient objects when the context is not clear . But looking at the keys might be more relevant when the objective is 'to find the treasure'.

a valuable reference for creating a lightweight virtual disaster response environment.

Other works like [A38], focus on extracting relevant features templates from task-specific semantic memory of objects. These templates bias the bottom-up attention map towards top-down relevant objects. An approach like this is necessary and highly relevant, but since it is largely based on computer vision and feature extraction, it quickly gets out of the scope of this study and thesis. It might be prudent for the thesis to assume that good approaches to complete such tasks [A29] [A23] [A36] [A55] already exist but may need trivial modifications to support human interventions (section 4). This would allow for more focus on planning and decision-making.

Semantic labelling

Semantics refer to the labels or categories humans assign to objects for classification. As opposed to object detection, which is mainly used for feature localization, semantic segmentation gives a class for each pixel in the image and is therefore more fine grained. From an information perspective, semantic segmentation can be viewed as a compression task since it filters out details like shadows and lighting, retaining essential geometrical information such as edges. In tasks like target search, where nuanced details are not crucial, this compression is useful for decision-making at a high level [A29]. A further study found that when performing tasks, humans even involuntarily suppressed salient features in favour of experience based semantic features related to the task [A28].

Semantics can be used to encode both bottom-up and top-down attention tasks. For instance, in [A3], semantics are used to group properties like specularity in the scene which are detrimental for Visual Inertial Odometry (VIO) localisation. Contrarily, in [A17], object detection is used in 2D but a 3D semantic voxel map is made from these detections. The authors then use a resolution based metric called area per pixel to focus on objects of interest while simultaneously exploring the space. However, resolving pixels in a robot's Field of View (FOV) does not guarantee uncovering occluded areas or the act of 'finding' objects of interest. Moreover, it is likely that some objects are more important than others and the desired resolution might be a function of these priorities. However, the idea that regions of interest in 2D can be projected to 3D voxels is very relevant. This idea of projection could be combined with 2D saliency views sourced from semantic relationships [A29] [A55] to create global 'attention maps' in metric space for viewpoint planning.

Target navigation is often used in structured indoor settings [A39] [A10] for object-labelling or embodiment tasks. In [A39], knowledge graphs and DRL is used to navigate to a 2D 'target' scene. The use of spatial relationships between semantic objects is interesting but it is the highly structured environment that enables these relationships to be formed and learned. In [A10], a notion of curiosity about an object is developed based on consistency in object identification scores across multiple spatio-temporal views. The idea of object curiosity and detection uncertainty is interesting and relevant. It could be combined with an approach to rank objects [A22] along with human input to create 'contextually ranked curiosities' for each object and guide the robot near probable target areas. This also lines up with the hierarchical planning approach in [A60] and [A7] where coarse plans are created first and then viewpoints are refined locally. Some key points relevant to indoor settings were noted:

- Firstly, for structured indoor environments, datasets like MatterPort3d [A9], Robo-VLN [A34] exist which can accelerate research. For cluttered outdoor scenarios like SAR or wildlife rescue, it is non-trivial to create such datasets and learn generalised policies for them. This means that real-time simulations of the right perceptual fidelity are a more appropriate tool for testing algorithms as opposed to datasets.

- Secondly, there are many works that use semantics to first segment rooms or create object-room relations [A59] [A30], and then perform local search within rooms. The first problem is a very specific domain in itself, and to refine the topic, this study only focuses on the latter. It is assumed that a target room with multiple cluttered objects has been selected and a fixed number of robots are present to carry out local search within the room. This simplification also allows us to use semantics/object detection independently for each robot's FOV.

There also exist other works in fields like inspection path planning and 3d scene reconstruction which are not directly related but have shared concepts. For instance, a recent work [A21] creates TSP tours around semantically segmented meshes for 3D objects to inspect the surface. This combination of viewpoint sampling around the object [A45] and a local TSP tour is a very powerful and reliable framework for planning tasks in real environments. The work in [A45] also uses a multi-resolution TSDF representation to account for imperfect depth sensing during 3D reconstruction.

2.3 Conclusions

Exploration

The exploration problem is widely studied in literature and a useful summary of key techniques that allow these algorithms to be deployed on real systems with hardware constraints is given below:

- Deterministic yaw optimization: In [A56], the authors explain that sampling 2.5D poses (x, y, z, θ) as viewpoints is problematic because the ideal yaw angle θ for a viewpoint in space depends on the frontiers/boundaries. Instead they use a deterministic yaw policy which optimizes the yaw angles such that they always cover the maximum number of voxels in view. This is a 'good-enough' solution because it is not pedantic about the quality and can therefore be deployed on actual systems as demonstrated by future research [A60] [A16].

- Frontier information structures: In [A60], the authors come up with the notion of Frontier information structures (FIS) which enable frontiers to carry necessary information about it's surroundings like candidate viewpoints, bounding boxes etc. Endowing these high level structures with more information allows the robot to do fine grained decision making without sampling too many points. It is interesting to see that simple changes in software like data structures can greatly influence the system as whole.

- Sparse ray casting and caching: In [A49], the authors prove that the ray-casting step that is necessary to evaluate the utility of a viewpoint, can be done at a fraction of the computational cost without a large performance cost. This technique has also been used in above papers like [A56] [A60] [M32] [A16].

- Open loop TSP tours: In the work by [A41], and subsequently in [A60] [M32], it is observed that high-level structures such as frontiers are far and may undergo changes as the robot moves. Consequently, only coarse global plans are deemed necessary for these structures, which can be done using Open loop tours of the Travelling Salesman Problem (TSP). The key focus here is to pick important nodes within each frontier cluster, and there are several creative methods to accomplish this. In addition to their computational efficiency, discrete combinatorial approaches, like TSPs, are reliable and easily explainable. The integration of human interventions also becomes straightforward as it only requires the rearrangement of nodes and the computation of a new tour.

It's important to note that the above considerations focus solely on exploration (treating all regions as equally important i.e. no targets), and does not involve dividing the workload among multiple robots.

Target search

- Visual attention is not isolated to just bottom-up or top-down approaches. Akin to human vision, the intrinsic pull of objects from the environment must be combined with task relevant top-down priorities (either from human interventions or knowledge bases). Since fields like computer vision and NLP fall out of the scope of this study, it might be wise to assume the existence of a attention map source or use task-relevant ground truth data.

- Semantics enable information compression in RGB images while preserving sufficient data for path planning. They are also relevant to forming spatial object relationships on global maps and creating visual-language models [A58]. However, the scope of this study will be limited to using semantics only for informative navigation, assuming the presence of robust semantic segmentation pipeline. The specific way in which semantics are used will be left as a question to be addressed in the thesis. Some relevant works such as [A55], [A17], and [A10] can be referred to for integrating semantics.

- Unlike static image processing tasks like object classification or dataset creation for structured indoor environments, active perception tasks require dynamic simulation environments [A48] [A39]. This motivates the selection of a simulation environment which is computationally efficient, has the right perceptual fidelity (not too high, not too low), and is easy to interface with frameworks like ROS. Most works use simulators like Gazebo which might also be an appropriate choice for this work.

- In the wider context of the thesis and with conclusions from section 2.1, finding objects of interest in an unknown environment can be treated as an augmented exploration problem where all areas/objects are not equally important. This essentially means setting priorities from top-down attention and re-ordering the planned tours in a sensible manner. To adapt a TSP for target search however, the visitation order of nodes should account for distance as well as other costs like object priorities/information gain. This is achieved using heuristics in literature [A60] [A33] [A41].

References (A)

[A1] R. Bajcsy. Active perception. *Proceedings of the IEEE*, 76(8):966–1005, August 1988. Conference Name: Proceedings of the IEEE.

[A2] Ruzena Bajcsy, Yiannis Aloimonos, and John K. Tsotsos. Revisiting active perception. *Autonomous Robots*, 42(2):177–196, February 2018.

[A3] Luca Bartolomei, Lucas Teixeira, and Margarita Chli. Perception-aware path planning for uavs using semantic segmentation. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 5808–5815. IEEE, 2020.

[A4] Graeme Best. Planning Algorithms for Multi-Robot Active Perception. January 2019.

[A5] Andreas Bircher, Mina Kamel, Kostas Alexis, Helen Oleynikova, and Roland Siegwart. Receding horizon" next-best-view" planner for 3d exploration. In *2016 IEEE international conference on robotics and automation (ICRA)*, pages 1462–1468. IEEE, 2016.

[A6] Sean Bone, Luca Bartolomei, Florian Kennel-Maushart, and Margarita Chli. Decentralised multi-robot exploration using monte carlo tree search. In *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 7354–7361. IEEE, 2023.

[A7] Chao Cao, Hongbiao Zhu, Howie Choset, and Ji Zhang. TARE: A Hierarchical Framework for Efficiently Exploring Complex 3D Environments. In *Robotics: Science and Systems XVII*. Robotics: Science and Systems Foundation, July 2021.

[A8] Andrea Carbone, Daniele Ciacelli, Alberto Finzi, and Fiora Pirri. Autonomous Attentive Exploration in Search and Rescue Scenarios. In Lucas Paletta and Erich Rome, editors, *Attention in Cognitive Systems. Theories and Systems from an Interdisciplinary Viewpoint*, volume 4840, pages 431–446. Springer Berlin Heidelberg, Berlin, Heidelberg, 2007. Series Title: Lecture Notes in Computer Science.

[A9] Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Niessner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang. Matterport3d: Learning from rgb-d data in indoor environments. *International Conference on 3D Vision (3DV)*, 2017.

[A10] Devendra Singh Chaplot, Helen Jiang, Saurabh Gupta, and Abhinav Gupta. Semantic curiosity for active visual learning. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part VI 16*, pages 309–326. Springer, 2020.

[A11] Benjamin Charrow, Sikang Liu, Vijay Kumar, and Nathan Michael. Information-theoretic mapping using cauchy-schwarz quadratic mutual information. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pages 4791–4798. IEEE, 2015.

[A12] Titus Cieslewski, Elia Kaufmann, and Davide Scaramuzza. Rapid exploration with multi-rotors: A frontier selection method for high speed flight. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 2135–2142. IEEE, 2017.

[A13] Cl Connolly. The determination of next best views. In *Proceedings. 1985 IEEE international conference on robotics and automation*, volume 2, pages 432–435. IEEE, 1985.

[A14] Pablo Covarrubias, Ángel Andrés Jiménez, Felipe Cabrera, and Alan Costall. The senses considered as perceptual systems: the revolutionary ideas of gibson's 1966 book, 50 years later-part 1, 2017.

[A15] Céline Craye, David Filliat, and Jean-François Goudou. RL-IAC: An exploration policy for online saliency learning on an autonomous mobile robot. In *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 4877–4884, October 2016. ISSN: 2153-0866.

[A16] Anna Dai, Sotiris Papatheodorou, Nils Funk, Dimos Tzoumanikas, and Stefan Leutenegger. Fast frontier-based information-driven autonomous exploration with an mav. In *2020 IEEE international conference on robotics and automation (ICRA)*, pages 9570–9576. IEEE, 2020.

[A17] Tung Dang, Christos Papachristos, and Kostas Alexis. Autonomous exploration and simultaneous object search using aerial robots. In *2018 IEEE Aerospace Conference*, pages 1–7, March 2018.

[A18] Tung Dang, Christos Papachristos, and Kostas Alexis. Visual Saliency-Aware Receding Horizon Autonomous Exploration with Application to Aerial Robotics. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 2526–2533, Brisbane, QLD, May 2018. IEEE.

[A19] Tung Dang, Marco Tranzatto, Shehryar Khattak, Frank Mascarich, Kostas Alexis, and Marco Hutter. Graph-based subterranean exploration path planning using aerial and legged robots. *Journal of Field Robotics*, 37(8):1363–1388, 2020. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/rob.21993.

[A20] Alessandro Devo, Jeffrey Mao, Gabriele Costante, and Giuseppe Loianno. Autonomous Single-Image Drone Exploration With Deep Reinforcement Learning and Mixed Reality. *IEEE Robotics and Automation Letters*, 7(2):5031–5038, April 2022.

[A21] Mihir Dharmadhikari and Kostas Alexis. Semantics-aware Exploration and Inspection Path Planning. In *2023 IEEE International Conference on Robotics and Automation (ICRA)*, pages 3360–3367, London, United Kingdom, May 2023. IEEE.

[A22] Per-Erik Forssén, David Meger, Kevin Lai, Scott Helmer, James J Little, and David G Lowe. Informed visual search: Combining attention and object recognition. In *2008 IEEE International Conference on Robotics and Automation*, pages 935–942. IEEE, 2008.

[A23] Bashir Ghariba, Mohamed S Shehata, and Peter McGuire. Visual saliency prediction based on deep learning. *Information*, 10(8):257, 2019.

[A24] James Jerome Gibson. The senses considered as perceptual systems. 1966.

[A25] Héctor H González-Banos and Jean-Claude Latombe. Navigation strategies for exploring indoor environments. *The International Journal of Robotics Research*, 21(10-11):829–848, 2002.

[A26] Qiao Gu, Alihusein Kuwajerwala, Sacha Morin, Krishna Murthy Jatavallabhula, Bipasha Sen, Aditya Agarwal, Corban Rivera, William Paul, Kirsty Ellis, Rama Chellappa, et al. Conceptgraphs: Open-vocabulary 3d scene graphs for perception and planning. *arXiv preprint arXiv:2309.16650*, 2023.

[A27] Anna Guerra, Francesco Guidi, Davide Dardari, and Petar M. Djuric. Reinforcement Learning for UAV Autonomous Navigation, Mapping and Target Detection. In *2020 IEEE/ION Position, Location and Navigation Symposium (PLANS)*, pages 1004–1013, Portland, OR, USA, April 2020. IEEE.

[A28] Taylor R. Hayes and John M. Henderson. Scene semantics involuntarily guide attention during visual search. *Psychonomic Bulletin & Review*, 26(5):1683–1689, October 2019.

[A29] Taylor R. Hayes and John M. Henderson. Looking for Semantic Similarity: What a Vector-Space Model of Semantics Can Tell Us About Attention in Real-World Scenes. *Psychological Science*, 32(8):1262–1270, August 2021. Publisher: SAGE Publications Inc.

[A30] Alejandra C. Hernandez, Erik Derner, Clara Gomez, Ramon Barber, and Robert Babuška. Efficient Object Search Through Probability-Based Viewpoint Selection. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 6172–6179, October 2020. ISSN: 2153-0866.

[A31] Dirk Holz, Nicola Basilico, Francesco Amigoni, and Sven Behnke. Evaluating the efficiency of frontier-based exploration strategies. In *ISR 2010 (41st International Symposium on Robotics) and ROBOTIK 2010 (6th German Conference on Robotics)*, pages 1–8. VDE, 2010.

[A32] Armin Hornung, Kai M Wurm, Maren Bennewitz, Cyrill Stachniss, and Wolfram Burgard. Octomap: An efficient probabilistic 3d mapping framework based on octrees. *Autonomous robots*, 34:189–206, 2013.

[A33] Junlong Huang, Boyu Zhou, Zhengping Fan, Yilin Zhu, Yingrui Jie, Longwei Li, and Hui Cheng. FAEL: Fast Autonomous Exploration for Large-scale Environments With a Mobile Robot. *IEEE Robotics and Automation Letters*, 8(3):1667–1674, March 2023.

[A34] Muhammad Zubair Irshad, Chih-Yao Ma, and Zsolt Kira. Hierarchical cross-modal agent for robotics vision-and-language navigation. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pages 13238–13246. IEEE, 2021.

[A35] S. Kastner and L. G. Ungerleider. The neural basis of biased competition in human visual cortex. *Neuropsychologia*, 39(12):1263–1276, 2001.

[A36] Iuliia Kotseruba and John K Tsotsos. Understanding and modeling the effects of task and context on drivers' gaze allocation. *arXiv preprint arXiv:2310.09275*, 2023.

[A37] Mikko Lauri and Risto Ritala. Planning for robotic exploration based on forward simulation. *Robotics and Autonomous Systems*, 83:15–31, 2016.

[A38] Dong Liu, Ming Cong, Yu Du, and de Silva Clarence W. GMM-based visual attention for target selection of indoor robotic tasks. *Industrial Robot: An International Journal*, 40(6):583–596, January 2013. Publisher: Emerald Group Publishing Limited.

[A39] Yunlian Lv, Ning Xie, Yimin Shi, Zijiao Wang, and Heng Tao Shen. Improving Target-driven Visual Navigation with Attention on 3D Spatial Relationships, April 2020. arXiv:2005.02153 [cs, stat].

[A40] Daniel Mellinger and Vijay Kumar. Minimum snap trajectory generation and control for quadrotors. In *2011 IEEE international conference on robotics and automation*, pages 2520–2525. IEEE, 2011.

[A41] Zehui Meng, Hailong Qin, Ziyue Chen, Xudong Chen, Hao Sun, Feng Lin, and Marcelo H. Ang. A Two-Stage Optimized Next-View Planning Framework for 3-D Unknown Environment Exploration, and Structural Reconstruction. *IEEE Robotics and Automation Letters*, 2(3):1680–1687, July 2017. Conference Name: IEEE Robotics and Automation Letters.

[A42] Huan Nguyen, Rasmus Andersen, Evangelos Boukas, and Kostas Alexis. Uncertainty-aware visually-attentive navigation using deep neural networks. *The International Journal of Robotics Research*, page 02783649231218720, December 2023. Publisher: SAGE Publications Ltd STM.

[A43] Farzad Niroui, Kaicheng Zhang, Zendai Kashino, and Goldie Nejat. Deep reinforcement learning robot for search and rescue applications: Exploration in unknown cluttered environments. *IEEE Robotics and Automation Letters*, 4(2):610–617, 2019.

[A44] Farzad Niroui, Kaicheng Zhang, Zendai Kashino, and Goldie Nejat. Deep Reinforcement Learning Robot for Search and Rescue Applications: Exploration in Unknown Cluttered Environments. *IEEE Robotics and Automation Letters*, 4(2):610–617, April 2019. Conference Name: IEEE Robotics and Automation Letters.

[A45] Sotiris Papatheodorou, Nils Funk, Dimos Tzoumanikas, Christopher Choi, Binbin Xu, and Stefan Leutenegger. Finding Things in the Unknown: Semantic Object-Centric Exploration with an MAV. In *2023 IEEE International Conference on Robotics and Automation (ICRA)*, pages 3339–3345, May 2023.

[A46] Vasili Ramanishka, Abir Das, Jianming Zhang, and Kate Saenko. Top-Down Visual Saliency Guided by Captions. pages 7206–7215, 2017.

[A47] Amir Rasouli, Pablo Lanillos, Gordon Cheng, and John K Tsotsos. Attention-based active visual search for mobile robots. *Autonomous Robots*, 44(2):131–146, 2020.

[A48] Lukas Schmid, Michael Pantic, Raghav Khanna, Lionel Ott, Roland Siegwart, and Juan Nieto. An Efficient Sampling-Based Method for Online Informative Path Planning in Unknown Environments. *IEEE Robotics and Automation Letters*, 5:1–1, January 2020.

[A49] Magnus Selin, Mattias Tiger, Daniel Duberg, Fredrik Heintz, and Patric Jensfelt. Efficient autonomous exploration planning of large-scale 3-d environments. *IEEE Robotics and Automation Letters*, 4(2):1699–1706, 2019.

[A50] Lei Tai and Ming Liu. Towards Cognitive Exploration through Deep Reinforcement Learning for Mobile Robots, October 2016. arXiv:1610.01733 [cs].

[A51] Tong Tao, Yalou Huang, Fengchi Sun, and Tingting Wang. Motion planning for slam based on frontier exploration. In *2007 International Conference on Mechatronics and Automation*, pages 2120–2125. IEEE, 2007.

[A52] John K. Tsotsos. On the relative complexity of active vs. passive visual search. *International Journal of Computer Vision*, 7(2):127–141, January 1992.

[A53] Hassan Umari and Shayok Mukhopadhyay. Autonomous robotic exploration based on multiple rapidly-exploring randomized trees. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 1396–1402, September 2017. ISSN: 2153-0866.

[A54] Dirk Walther, Ueli Rutishauser, Christof Koch, and Pietro Perona. Selective visual attention enables learning and recognition of multiple objects in cluttered scenes. *Computer Vision and Image Understanding*, 100(1-2):41–63, 2005.

[A55] Xia Wang, Haibing Yin, Yu Lu, Shiling Zhao, and Yong Chen. Semantically Adaptive JND Modeling with Object-Wise Feature Characterization, Context Inhibition and Cross-Object Interaction. *Sensors*, 23(6):3149, January 2023. Number: 6 Publisher: Multidisciplinary Digital Publishing Institute.

[A56] Christian Witting, Marius Fehr, Rik Bähnemann, Helen Oleynikova, and Roland Siegwart. History-aware autonomous exploration in confined environments using mavs. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 1–9. IEEE, 2018.

[A57] Brian Yamauchi. A frontier-based approach for autonomous exploration. In *Proceedings 1997 IEEE International Symposium on Computational Intelligence in Robotics and Automation CIRA'97.'Towards New Computational Principles for Robotics and Automation'*, pages 146–151. IEEE, 1997.

[A58] Haotian* Zhang, Pengchuan* Zhang, Xiaowei Hu, Yen-Chun Chen, Liunian Harold Li, Xiyang Dai, Lijuan Wang, Lu Yuan, Jenq-Neng Hwang, and Jianfeng Gao. Glipv2: Unifying localization and vision-language understanding. *arXiv preprint arXiv:2206.05836*, 2022.

[A59] Kaiyu Zheng, Rohan Chitnis, Yoonchang Sung, George Konidaris, and Stefanie Tellex. Towards Optimal Correlational Object Search. In *2022 International Conference on Robotics and Automation (ICRA)*, pages 7313–7319, May 2022.

[A60] Boyu Zhou, Yichen Zhang, Xinyi Chen, and Shaojie Shen. FUEL: Fast UAV Exploration Using Incremental Frontier Structure and Hierarchical Planning. *IEEE Robotics and Automation Letters*, 6(2):779–786, April 2021. Conference Name: IEEE Robotics and Automation Letters.

Chapter 3

Coordination

Exploration and target searching in emergency response scenarios are inherently time-sensitive tasks. Using multiple vehicles that can coordinate their actions and decisions can reduce completion time, increase fault-tolerance [M13], and also provide complementary observations from wider spatial viewpoints [A4]. Moreover, for some exploration settings like caves, multiple heterogenous robots teams with multi-modal sensing and actuation might be the only possible solution [M22] [M15]. However, using more robots adds complexity and if actions are not coordinated in a sensible manner, it can lead to decreased performance and overlapping exploration areas. Current research in multi robot systems for exploration can be divided into three subfields:

- Planning and Coordination: Coordination implies that even though a task can be performed by a single robot alone, if N robots get together to do it, the efficiency of the system would grow with the number of robots. It's easy to see the utility for exploration because the *coverage* of a bounded volume is an elementary unit that scales easily with the number of robots.

- Shared perception: Certain tasks require collaboration of robots with diverse architectures and functionalities to accomplish tasks that many units of either robot type A or type B could not achieve independently [M1]. For instance, rescuing a lost human in a forest at night might require a drone with infrared camera to geo-locate the target and a ground robot with a pointcloud sensor to provide near field situational awareness. A human providing object priorities remotely could also be seen as collaborative shared perception.

- Communication: A common research area is the communication architecture – Decentralised vs. Centralised. Decentralised communication is preferable because it provides fault tolerance and distribution of compute [M16]. However, centralised architectures are simpler, do not suffer from localization and mapping inconsistencies and rely less on communication hardware.

Review Methodology

There is a lot of intersection among the three fields and while relevant papers are included, the scope of this study and research is limited to coordination using homogeneous drones. Collaborative perception is discussed briefly in section 3.2 and communication architectures are mentioned as well but not as a separate section. An interesting gap that was noticed at the literature retrieval stage was that while multiple robots are being increasingly deployed for exploration, very few works focus on combining active perception for simultaneous target search. **Keywords**: multi-robot exploration, coordination, multi-robot target search, shared perception, decentralised exploration, map sharing.

3.1 Planning and coordination

The main motivation for coordination in exploration is to limit re-exploration and reduce overlap among areas. This is most often done by optimal redistribution of viewpoints to minimize costs like time or overlapping area.

LLoyd algorithms: A big field of research for coverage path planning comes under the category of LLoyd algorithms. These algorithms partition the entire area into convex regions of equal area and assign robots to them [M23] [M12]. These methods are also often used to establish an optimal mesh network for communication coverage in disaster scenarios. Further advancements which consider target areas use methods like Morse decomposition to divide the area [M4]. However, these algorithms assume perfect communication, existence of a map and often lead to uneven workload assignment [M16]. Moreover, these algorithms are only relevant from an exploration perspective and not target search because the main goal is complete coverage of the map.

Task assignment and allocation: Initial naive approaches for multi-robot exploration used greedy assignment of target frontiers [M26], which do not consider workload balancing or communication limitations. In [M9], a high quality single robot plan is computed over viewpoints and it is broken up into N parts and assigned to all robots. This is done in a naive centralised fashion but the experimental testing and evaluation from the work is interesting. Improvements in task assignment extend greedy assignment with distributed computation [M5]. Here, a subset of the global plans are assigned to a fixed number of robots across multiple rounds. This is done on each robot and bounds on suboptimality are given.

Auction based methods are first introduced in [M33] where the coordination problem is formulated using the principle of market economy. Each robot places it's own tasks on auction and other robots (bidders) can trade these tasks based on expected profit values. In [M20], centralised auctions are held to move more multiple robots to semantically informed relevant areas for a search and rescue scenario. The work in [M7] provides a good overall review of market based approaches and [M18] gives an experimental evaluation for different auction objectives used for multi-robot object-search task. As a sidenote, the latter work is also a great reference for setting up statistical object-centric exploration experiments.

In general, auction based approaches are decentralised and require low bandwidth requirement because of the small scalar packet size [M18] which makes them attractive for agile aerial vehicles. The main drawback of these methods is that they are less robust to unstable communication [M32] and require frequent replanning to maintain consistency of the allocation over time [M16].

Pairwise optimization: Realising some limitations of market-based approaches, and real world communication limitations of robotic sensor networks, an initial work in [M11] create a pairwise partitioning strategy. Here, the robots represent the environment as a graph and whenever two robots meet, they merge graphs and compute two new graphs which minimize the combined cost. The approach is guaranteed to converge over time and requires very less communication. This work inspired a number of state of the art approaches to multi robot exploration with changes to the optimization variable (graphs vertices in [M11]). In [M16], pairwise optimization is used to compute sets of optimal open-loop TSP tours across frontiers. To reduce computation overhead, the authors use a workload balancing algorithm which exchanges single targets among robots and uses local hill descent to optimize partitions. This approach is further used in [M32], but the elementary unit of exchange is a coarse hierarchical grid (hgrid) that partitions the bounded volume. This coarse hgrid means that the power set of all possible partitions is small, and an optimal allocation can be achieved instead of approximation using local hill descent. Other relevant approaches use pairwise optimization for either distributing frontier points in a locally sampled region [M14] or use regions of attractions [M2] by using a different cost function than [M32].

Since pairwise techniques were created to overcome real-world limitations and push for decentralisation, a common theme across all the works is their ability to extend simulations to hardware experiments. This is also a key motivation to adopt such methods for the thesis.

Learning based methods: Learning based methods like multi-agent reinforcement learning for visual navigation seem attractive owing to rapid developments in architectures and datasets over the past decade. In [M28], the authors formulate a asynchronous version of a Decentralised Partially Observable Markov Decision Process (Dec-POMDP), but the state and observation spaces have low dimensions and the robot is also simple. In [M29], a transformer based architecture is used to extend the active neural slam framework to multi agent settings. In [M17], semantics are used to train a policy for finding a visual target object. This work exploits the prior semantic object-object relationships very well to search for key objects in the environment. It could be used as a reference for creating such relationships for an emergency response scenario. However, in the above papers and similar literature, the results are limited to simulated indoor datasets which are highly structured and do not generalise to noisy real-life scenarios. In this light, more deterministic methods like pairwise optimization or auction methods are recommended for bridging the sim-to-real gap.

Miscelleaneous: Subtopics that don't belong to a specific category or are out of scope are mentioned for the sake of completeness. In [M30], the authors create a potential field to assign multiple robots to targets, but the results are limited to 2D indoor scenarios. In [M3] a decentralised variant of Monte Carlo Tree Search (MCTS) is developed for multi robot active perception. Methods like these optimize the entire sequence of actions for all robots in a joint optimization problem. While the work has other relevant results and findings, techniques like MCTS can face problems of scalability to higher dimensions or longer horizons in real environments.

SAR environments are not limited to cluttered areas like mines [M22] but also include open areas like forests [M2], and mountains [M24]. A common trend in such environments is to use multi-rotors with downward facing cameras or fixed-wing UAVs. Notably, this change in the platform and environment also changes coordination strategies. Here, local methods like pairwise optimization or auctions are not the best strategy and coordination is done at a very global scale with more focus on exhaustive search [M24] and mission-management [M6].

3.2 Collaborative perception

A substantial advantage that multiple robots can provide is shared perception of the environment. This can reduce target detection uncertainty, and help gather data faster. In a centralised communication architecture, a global map is maintained, and observations are not shared among the robots. The push for decentralisation makes this problem harder because not only state information like poses need to be exchanged but also partial observations of the map. This can become a significant bottleneck on resource limited aerial vehicles with low power sensors like Wi-fi. Consequently, much of the research in this field focuses on making this data exchange more efficient.

In [M31], instead of exchanging local grid maps, light topological graph representations of the environment are used. An improvement in [M8], incorporates richer representations by using Gaussian Mixture Models. Both works report very low memory usage and advocate performance in restricted communication environments.

Two relevant works that stand out for their good experimental results are [M27] and [M32]. In [M27], each robot shares segments of point clouds and merges them into a global map which is then used for relative pose estimation. This is done in a centralised fashion. In contrast, in [M32] drones can exchange map chunks (local occupancy grids) with their neighbours in a decentralised manner. An Ultra Wide Band (UWB) module is used as the communication hardware and unreliablilty is dealt with using software techniques like shared bookkeeping and syncing. Both works give reliable results in complex real world environments.

An interesting direction here would be to explore a novel exchange representation specifically designed for semantic target search, such as segmenting objects from point clouds for localisation [M10]. Another consideration is exchanging high-level information like confidence scores of class labels, and using these to influence object-object relationships [M19]. This approach could provide a straightforward method to reach a consensus regarding object priorities even if the same objects are detected by different robots from different viewpoints (fig 3.1).

Note that fields like Multi-Robot SLAM, data association, and place recognition

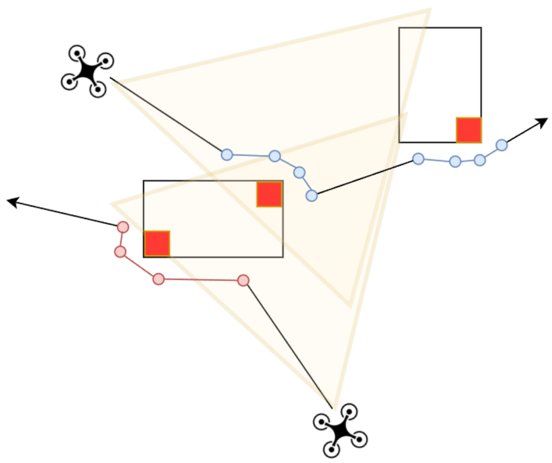

Figure 3.1: Shared perception and coordination with multiple drones

encompass detailed efforts in collaborative perception. These works are not covered here because the scope is limited to perception techniques that are relevant for planning.

3.3 Conclusions

The following conclusions and summary can be derived from the above literature:

- Stochastic environments like SAR require reliable multi-robot coordination even in the presence of unreliable communication. Presently, end-to-end learning-based methods struggle with generalisation in such scenarios. Combinatorial optimization methods for coordination like auctions or pairwise partitioning can assist human operators in fine-tuning decisions and making them explainable.

- When doing a mission which involves target search, semantically informed coordination decisions can help improve the overall system efficiency [M20]. In this light, it might be useful to explore exchangeable data structures among drones that are relevant to semantic target search. As discussed in the previous section these could be segmented point clouds, probability distributions over detection confidence scores, and similar data. These techniques could help reduce the detection uncertainty of targets and accelerate the search process.

- Approaches such as pairwise optimization or auction based methods can make the system decentralised and robust to uncertain environments. However, these algorithms are designed to minimize overlapping areas during exploration, leading to robots staying far apart from each other [M33]. Contrarily, while doing target search, there might be situations where a group of interesting objects are placed close together and optimal resource allocation would demand that multiple robots look at the same local regions with close spatial viewpoints (fig. 3.1). This demands coordination at a more localized level, posing challenges in adapting state-of-the-art algorithms like [M32], which rely on hgrids. Approaches like [M27] may offer more utility in such scenarios, although the subspace within sub-map concept could be excessive for smaller cluttered spaces.

To develop this further, the subspace could be modified to be an axis aligned bounding box around the group of interesting objects and distributing raw viewpoints within each subspace may prove satisfactory. Additionally, object-centric multi-robot active perception methods which use graphs could be beneficial [A4]. This presents a potential gap that could be explored in future work, branching off from the active perception problem in the thesis.

References (M)

[M1] Coordination, Cooperation, and Collaboration with Vijay Kumar, howpublished = https://robohub.org/coordination-cooperation-and-collaboration/,.

[M2] Luca Bartolomei, Lucas Teixeira, and Margarita Chli. Fast Multi-UAV Decentralized Exploration of Forests. *IEEE Robotics and Automation Letters*, 8(9):5576–5583, September 2023. Conference Name: IEEE Robotics and Automation Letters.

[M3] Graeme Best, Oliver M Cliff, Timothy Patten, Ramgopal R Mettu, and Robert Fitch. Dec-MCTS: Decentralized planning for multi-robot active perception. *The International Journal of Robotics Research*, 38(2-3):316–337, March 2019.

[M4] Chang Cai, Jianfeng Chen, Muhammad Saad Ayub, and Fen Liu. A Task Allocation Method for Multi-AUV Search and Rescue with Possible Target Area. *Journal of Marine Science and Engineering*, 11(4):804, April 2023. Number: 4 Publisher: Multidisciplinary Digital Publishing Institute.

[M5] Micah Corah and Nathan Michael. Distributed matroid-constrained submodular maximization for multi-robot exploration: theory and practice. *Autonomous Robots*, 43(2):485–501, February 2019.

[M6] Edison Pignaton De Freitas, Maik Basso, Antonio Arlis Santos Da Silva, Marcos Rodrigues Vizzotto, and Mateus Schein Cavalheiro Correa. A Distributed Task Allocation Protocol for Cooperative Multi-UAV Search and Rescue Systems. In *2021 International Conference on Unmanned Aircraft Systems (ICUAS)*, pages 909–917, Athens, Greece, June 2021. IEEE.

[M7] M.B. Dias, R. Zlot, N. Kalra, and A. Stentz. Market-Based Multirobot Coordination: A Survey and Analysis. *Proceedings of the IEEE*, 94(7):1257–1270, July 2006. Conference Name: Proceedings of the IEEE.

[M8] Haolin Dong, Jincheng Yu, Yuanfan Xu, Zhilin Xu, Zhaoyang Shen, Jiahao Tang, Yuan Shen, and Yu Wang. Mr-gmmapping: Communication efficient multi-robot mapping system via gaussian mixture model. *IEEE Robotics and Automation Letters*, 7(2):3294–3301, 2022.

[M9] Christian Dornhege, Alexander Kleiner, Andreas Hertle, and Andreas Kolling. Multirobot Coverage Search in Three Dimensions. *Journal of Field Robotics*, 33(4):537–558, 2016. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/rob.21573.

[M10] Renaud Dube, Andrei Cramariuc, Daniel Dugas, Hannes Sommer, Marcin Dymczyk, Juan Nieto, Roland Siegwart, and Cesar Cadena. Segmap: Segment-based mapping and localization using data-driven descriptors. *The International Journal of Robotics Research*, 39(2-3):339–355, 2020.

[M11] Joseph W. Durham, Ruggero Carli, Paolo Frasca, and Francesco Bullo. Discrete Partitioning and Coverage Control for Gossiping Robots. *IEEE Transactions on Robotics*, 28(2):364–378, April 2012. arXiv:1011.1939 [cs, math].

[M12] Dominik Haumann, Volker Willert, and Kim D Listmann. Discoverage: from coverage to distributed multi-robot exploration. *IFAC Proceedings Volumes*, 46(27):328–335, 2013.

[M13] Junyan Hu, Hanlin Niu, Joaquin Carrasco, Barry Lennox, and Farshad Arvin. Voronoi-Based Multi-Robot Autonomous Exploration in Unknown Environments via Deep Reinforcement Learning. *IEEE Transactions on Vehicular Technology*, 69(12):14413–14423, December 2020.

[M14] Yulin Hui, Xuewei Zhang, Hongming Shen, Hanchen Lu, and Bailing Tian. DPPM: Decentralized Exploration Planning for Multi-UAV Systems Using Lightweight Information Structure. *IEEE Transactions on Intelligent Vehicles*, pages 1–13, 2023.

[M15] Hiroaki Kitano, Satoshi Tadokoro, Itsuki Noda, Hitoshi Matsubara, Tomoichi Takahashi, Atsuhi Shinjou, and Susumu Shimada. Robocup rescue: Search and rescue in large-scale disasters as a domain for autonomous agents research. In *IEEE SMC'99 Conference Proceedings. 1999 IEEE International Conference on Systems, Man, and Cybernetics (Cat. No. 99CH37028)*, pages 739–743, 1999.

[M16] Lukas Klodt and Volker Willert. Equitable workload partitioning for Multi-Robot exploration through pairwise optimization. In *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 2809–2816, 2015.

[M17] Xinzhu Liu, Di Guo, Huaping Liu, and Fuchun Sun. Multi-Agent Embodied Visual Semantic Navigation with Scene Prior Knowledge, September 2021. arXiv:2109.09531 [cs].

[M18] Alejandro R. Mosteo and Luis Montano. Comparative experiments on optimization criteria and algorithms for auction based multi-robot task allocation. In *Proceedings 2007 IEEE International Conference on Robotics and Automation*, pages 3345–3350, April 2007. ISSN: 1050-4729.

[M19] O Martinez Mozos. Speeding-up multi-robot exploration by considering semantic place information. In *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.*, pages 1692–1697. IEEE, 2006.

[M20] Alberto Quattrini Li, Riccardo Cipolleschi, Michele Giusto, and Francesco Amigoni. A semantically-informed multirobot system for exploration of relevant areas in search and rescue settings. *Autonomous Robots*, 40(4):581–597, April 2016.

[M21] Jorge Pena Queralta, Jussi Taipalmaa, Bilge Can Pullinen, Victor Kathan Sarker, Tuan Nguyen Gia, Hannu Tenhunen, Moncef Gabbouj, Jenni Raitoharju, and Tomi Westerlund. Collaborative Multi-Robot Search and Rescue: Planning, Coordination, Perception, and Active Vision. *IEEE Access*, 8:191617–191643, 2020.

[M22] Marco Tranzatto, Frank Mascarich, Lukas Bernreiter, Carolina Godinho, Marco Camurri, Shehryar Khattak, Tung Dang, Victor Reijgwart, Johannes Loeje, David Wisth, Samuel Zimmermann, Huan Nguyen, Marius Fehr, Lukas Solanka, Russell Buchanan, Marko Bjelonic, Nikhil Khedekar, Mathieu Valceschini, Fabian Jenelten, Mihir Dharmadhikari, Timon Homberger, Paolo De Petris, Lorenz Wellhausen, Mihir Kulkarni, Takahiro Miki, Satchel Hirsch, Markus Montenegro, Christos Papachristos, Fabian Tresoldi, Jan Carius, Giorgio Valsecchi, Joonho Lee, Konrad Meyer, Xiangyu Wu, Juan Nieto, Andy Smith, Marco Hutter, Roland Siegwart, Mark Mueller, Maurice Fallon, and Kostas Alexis. CERBERUS: Autonomous Legged and Aerial Robotic Exploration in the Tunnel and Urban Circuits of the DARPA Subterranean Challenge, January 2022. arXiv:2201.07067 [cs].

[M23] Ling Wu, Miguel Ángel García García, Domenec Puig Valls, and Albert Solé Ribalta. Voronoi-based space partitioning for coordinated multi-robot exploration. 2007.

[M24] Linjie Xing, Xiaoyan Fan, Yaxin Dong, Zenghui Xiong, Lin Xing, Yang Yang, Haicheng Bai, and Chengjiang Zhou. Multi-uav cooperative system for search and rescue based on yolov5. *International Journal of Disaster Risk Reduction*, 76:102972, 2022.

[M25] Hao Xu, Yichen Zhang, Boyu Zhou, Luqi Wang, Xinjie Yao, Guotao Meng, and Shaojie Shen. Omni-swarm: A decentralized omnidirectional visual–inertial–uwb state estimation system for aerial swarms. *IEEE Transactions on Robotics*, 38(6):3374–3394, 2022.

[M26] Brian Yamauchi. Decentralized coordination for multirobot exploration. *Robotics and Autonomous Systems*, 29(2-3):111–118, 1999.

[M27] Jingtian Yan, Xingqiao Lin, Zhongqiang Ren, Shiqi Zhao, Jieqiong Yu, Chao Cao, Peng Yin, Ji Zhang, and Sebastian Scherer. MUI-TARE: Cooperative Multi-Agent Exploration with Unknown Initial Position. *IEEE Robotics and Automation*

Letters, pages 1–8, 2023. Conference Name: IEEE Robotics and Automation Letters.

[M28] Chao Yu, Xinyi Yang, Jiaxuan Gao, Jiayu Chen, Yunfei Li, Jijia Liu, Yunfei Xiang, Ruixin Huang, Huazhong Yang, Yi Wu, and Yu Wang. Asynchronous Multi-Agent Reinforcement Learning for Efficient Real-Time Multi-Robot Cooperative Exploration, April 2023. arXiv:2301.03398 [cs].

[M29] Chao Yu, Xinyi Yang, Jiaxuan Gao, Huazhong Yang, Yu Wang, and Yi Wu. Learning Efficient Multi-Agent Cooperative Visual Exploration, November 2022. arXiv:2110.05734 [cs].

[M30] Jincheng Yu, Jianming Tong, Yuanfan Xu, Zhilin Xu, Haolin Dong, Tianxiang Yang, and Yu Wang. Smmr-explore: Submap-based multi-robot exploration system with multi-robot multi-target potential field exploration method. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pages 8779–8785. IEEE, 2021.

[M31] Zhaoliang Zhang, Jincheng Yu, Jiahao Tang, Yuanfan Xu, and Yu Wang. Mr-topomap: Multi-robot exploration based on topological map in communication restricted environment. *IEEE Robotics and Automation Letters*, 7(4):10794–10801, 2022.

[M32] Boyu Zhou, Hao Xu, and Shaojie Shen. RACER: Rapid Collaborative Exploration With a Decentralized Multi-UAV System. *IEEE Transactions on Robotics*, 39(3):1816–1835, June 2023. Conference Name: IEEE Transactions on Robotics.

[M33] R. Zlot, A. Stentz, M.B. Dias, and S. Thayer. Multi-robot exploration controlled by a market economy. In *Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No.02CH37292)*, volume 3, pages 3016–3023 vol.3, May 2002.

Chapter 4

Humans in the Loop

Multi-robot teams can address a wide variety of challenges with state of the art coordination techniques, but there are still some aspects missing. Notably, it is the limitation of the single agent's intelligence that sets an upper bound on the overall system's capability. This is primarily because we are not close to achieving a fully generalised artificial mind that is capable of reasoning as humans do and cooperating as a species. Moreover, the idea that humans and machines are not comparable but complementary [H33] motivates the creation of semi-autonomous solutions where humans and robots share parts of autonomy, each performing what they can do best – often referred to as Human In The Loop (HITL). In situations like SAR, law enforcement etc., humans first responders can be considered better than robots at the following tasks:

- Situational and Contextual awareness: Humans are really good at extracting relevant information from the environment and building a contextual relations between objects – also called contextual awareness (CA) [H25] [H28]. Somewhat related, but distinct, situational awareness (SA) is defined as the perception, comprehension, and prediction of the elements of the environment in both time and space [H15]. The authors in [H25] and [H16], create a model for CA and SA for robots. CA is a mapping from the environment's measurements to the context (relevance of and relations between objects) and SA is the projection of this context into the future using the current 'situation' and state measurements.

- Adapting to uncertainty: Humans are good at adapting to changing environments and improvising plans [H2]. This ability is particularly useful in emergency response and SAR scenarios where environments are cluttered, dangerous, and unpredictable. Improvisation requires skills like satisficing and heuristics which promote approximate solutions [H23] and acceptance of errors due to cognitive flexibility [H9]. This can be seen as somewhat complementary to the previous point which demands anticipation and predictive reasoning [H23].

- Physical dexterity: Humans excel as master manipulators, both at fine levels, such as art, and coarse levels, like in warehousing. Environments such as reactor inspections, explosive handling, and mineral acquisition require a generalized set of limbs

– a capability currently unique to humans. Competitions like RoboCup rescue [1] and DARPA challenge [2] test these skills but since this primarily a mechanics/control problem, it is not explored in this study.

- Emotional intelligence: Perhaps, the hardest problem of all is to impart machines the same level of emotion and empathy that humans possess. We rely on context, subjective experience, and sometimes irrationality to guide decisions – all of which are considered sub-optimal from the perspective of an algorithmic machine. In emergency response, leveraging these human traits can be advantageous for biasing plans in favor of victims over material objects, which may be of lesser importance.

These unique capabilities show that there is a tangible place for a human member within a multi-robot team. The key here is then deciding how, and when to include this member within a team so that an human-robot collaboration principles like shared autonomy, workload, and trust are maintained [H34]. In the following sections, these structures and principles are explored in the context of human robot teams for emergency response for public safety and security.

Review methodology

The human factors research papers in this section are somewhat dated but still relevant, reflecting a limited evolution in our understanding over the past decade. Consequently, there is a higher proportion of older, more theoretical papers. This is also in part due to the relatively unexplored nature of the field of interventions and prioritised planning for search and rescue, offering ample scope and gaps to explore in the thesis. When including experimental works, care was taken that only statistically significant results are mentioned. In case a single paper's hypothesis seemed weak, multiple works were included which confirmed the hypothesis.

Keywords: Human-robot teaming in search and rescue, human vs. robot competencies, shared autonomy, situational/contextual awareness, workload, interventions, priority-aware planning.

4.1 Shared autonomy

Shared autonomy or mixed human-robot initiative teams are organisational structures where both humans and robots create a symbiotic relationship and contribute their competencies to achieve the goals of a task. This shared responsibility empowers the human to be vigilant, trust in their superior decision-making skills but still rely on the robot's superior autonomy and expendability to actually execute the task.

But as the complexity and autonomy of the overall robotic system increases, it becomes harder to incorporate a human member. In the case of multi-UAV teams managing multiple degrees of freedom and increased cognitive workload can cause confusion and

[1] https://rrl.robocup.org/

[2] https://www.darpa.mil/program/darpa-robotics-challenge

decrease performance [H10] [M21]. The work in [H30], shows that a mixed-initiative team with flexible coordination keeps the workload low. The authors in [H10] also found that deciding the level of automation is important and semi-autonomous solutions need to be explored to propel the field of human-robot SAR [H24].

Shared autonomy can have multiple levels of abstraction:

- Planning and control: At a lower level, the human operator can be in control of navigation and movement decisions for robot exploration. While this would allow more perceived situational awareness for the human and lesser autonomy [H1], it would also increase the workload [H30] [H26] and require frequent switching for small tasks like waypoint planning.

- Task control/decision-making: A task is a high level abstraction which is tied to a goal and involves low-level components like path planning, control, and perception. Decision support from the human in this task space could be setting target priorities, interventions to correct high-level goals [H6], and providing directional cues [H35]. Research in this area also includes modelling and learning human preferences, blending them with autonomous planners [H32]. In multi-robot SAR, this is relevant because objectives like deliberation and victim localization are nonlinear and context dependent, which humans excel at understanding. According to the authors in [H30], tasks can be given priorities by humans, and allocation can be performed autonomously among the robot team via decentralised coordination algorithms. In a similar vein, and perhaps the most relevant work for this subpoint, the authors in [H2] found that humans are best used for tasks like marking victims/targets and path-planning should be autonomous. This resulted in a statistically significant number of victims being marked. Furthermore, the authors observed that in scenarios involving multiple humans and robots, minimizing the intersection among the robot teams assigned to each human operator is advantageous. This idea of using human for encoding priorities is central to including the human-in-the-loop robot teams and it is further explored in section 4.2.

- Global behaviour coordination: In case of multiple robots, where the group might be controlled as a whole, humans can be used to set global formation patterns and collective behaviors [H11]. However, this is important when the number of robots is large compared to the number of operators, which is not the focus of this study. With lower robot numbers, area assignment is also an important problem [H4], but like section 2.2 explains it is assumed that this assignment has already been done and the number of robots to search a given area is fixed i.e. operating at the sub-scene level [H22].

- Shared workspace: A number of studies include the human in the same physical space as the robots [H17] [H4] [H13]. In [H4], multiple heterogeneous robots maintain connectivity with each other and guide the human with a tactile interface. The robots change roles when necessary and also explore targets simultaneously. The study is interesting from a system's perspective as real world experiments were conducted, but it employs a suboptimal greedy approach for planning. Moreover, it is hypothesized that including the humans in the robot space might actually be detrimental rather than effective because it is hard for either to predict the other's behaviour. The human competencies mentioned in the previous section can also be achieved by providing appropriate remote guidance. This limitation is also evident in [H13], where the robot's exploration is biased to the human's FOV, who is assumed to be static in a noise-less environment. However, the paper is a good reference for occlusion aware informative planning.

4.2 Priority encoding

The literature review in section 2.2 and human experience strongly points to the fact that when searching for objects of interest in an unknown environment, we do not search the whole area but use context and experience to narrow the search to only promising regions [A8] [A45]. Moreover, the research in [H8] shows that humans are more competent in noisy target identification compared to algorithms. This suggests that leveraging humans for providing target priorities is viable in both offline (context/situation) and online (interventions/requests) settings.

Offline: In offline settings, humans can give a-priori information about potential target locations. In [H31], this is done by setting priorities of nodes on a topological graph. In [M20] the authors use semantic prior information in a Multi Criteria Decision Making (MCDM) problem to evaluate the utility of various candidate robot locations. In [H19], the authors experiment with various blending techniques with prior knowledge and autonomous target search. However, the simulations are 2-dimensional owing to the use of particle filters and their scalability issues.

An interesting direction here is to *investigate how humans can establish situational context for an target detection task* before starting the search. There is surprisingly very little research on this and is limited to niche fields of image processing [H20] and/or natural-language processing [H29]. This could help in emergency response because every scenario will have a different set of salient objects for the robot. For instance, in a counter narcotics scenario a human can set prior context (`gun`, `white powder`) before the search starts. Techniques such as concept graphs [A26] can then extrapolate this context to assign priorities to storage containers like `bag` and `shelf` during the search, enabling more autonomy. An example of such a spatial concept graph is given in figure 4.1. This is considered a gap and while the field of image processing, Natural Language Processing (NLP), and saliency maps is out of scope, such ideas could still be developed from a planning and decision-making context [H8] [A8].

Online: While having an offline context is necessary for a certain level of autonomy and keeping operator workload low, emergency response scenarios are high demanding situations where the context is continuously changing, the situation needs to be re-evaluated frequently [H14]. This means that real-time online interventions from a human operator are also important.

The work in [H18] allows a multi robot system to work autonomously under normal

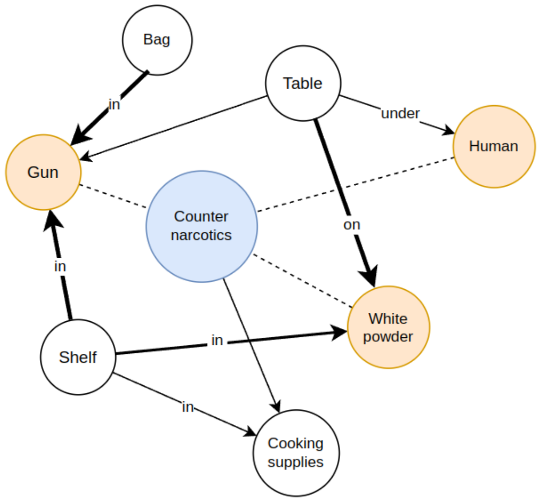

Figure 4.1: Spatial concept graph for Counter narcotics scenario

conditions and human assistance can be sought when a conflict arises. The authors claim that this method of sparse interventions combined with an adaptive autonomy interface can keep the workload low and situational awareness high. A highly relevant piece of work is [H8] where a human robot collaboration problem is formulated by balancing a human's visual ability with a robot's exploration ability. The robot's energy, access to a human operator's knowledge (formulated as questions), and target classification accuracy are formulated into a TSP optimization problem. Even though an initial drone pass is used to gain knowledge about the area, such a formulation is considered key to solving the problem. The targets can be given different priorities either coming from online interventions or from semantics relationships like in the previous section. Then, information gain techniques from 2.1 and saliency maps from 2.2 can be used to compute optimal tours. This would ensure that the top-down attention from a human operator can be used to plan prioritised paths and find targets quickly. The notion of superior human visual capability and including the human at the level of target identification is also confirmed by other works [H3] [H5].

In [H7], the authors propose an object substitution model where the robot can suggest semantically related candidates to the human in case the robot is unable to find the 'right' object. This allows the robot to adapt on-the-fly and continue operations. This concept of semantically related spatial graphs is commonly used in indoor environments (section 2.1), but not in situations like search and rescue because of the cluttered environment which could be a gap worth exploring.

As a side-note, learning from online human preferences is also interesting. Human-robot team operations in Urban Search and Rescue (USAR) and military contexts often extend over the long term, contrasting with Human-Robot Interaction for manufacturing [H34]. Therefore, leveraging data from real interactions becomes sensible for learning parameterized functions that can be reused and also improve preferences over time.

4.3 Conclusions

- Acquiring priorities for objects of interest from visual cues in an unknown environment is a great way to leverage human contextual and situational awareness while still using robot autonomy to carry out low-level tasks like path planning and coordination, thereby balancing both agent's competencies.

- Both offline context and online interventions can help in dealing with the dynamic nature of emergency response scenarios like SAR, law-enforcement, firefighting etc.

- An important challenge here is to go from human language like priorities/interventions to a planning context that robot can understand like information gain or reward [H6]. The semantic relationships and techniques like concept graphs [A26] which are trained based on human preferences could be useful here.

- While considering online interventions, it might be worth thinking about problems like flow interruption and what challenges come with actually including human input (which is known to be noisy [H27]) within the loop.

References (H)

[H1] Computational design of mixed-initiative human–robot teaming that considers human factors: situational awareness, workload, and workflow preferences - Matthew Gombolay, Anna Bair, Cindy Huang, Julie Shah, 2017.

[H2] Teams for Teams Performance in Multi-Human/Multi-Robot Teams, 2010.

[H3] Adaptive Autonomy in Human-on-the-Loop Vision-Based Robotics Systems | IEEE Conference Publication | IEEE Xplore, 2021.

[H4] Marco Aggravi, Giuseppe Sirignano, Paolo Robuffo Giordano, and Claudio Pacchierotti. Decentralized Control of a Heterogeneous Human–Robot Team for Exploration and Patrolling. *IEEE Transactions on Automation Science and Engineering*, 19(4):3109–3125, October 2022.

[H5] Arturo Miguel Russell Bernal and Jane Cleland-Huang. Hierarchically Organized Computer Vision in Support of Multi-Faceted Search for Missing Persons. In *2023 IEEE 17th International Conference on Automatic Face and Gesture Recognition (FG)*, pages 1–7, January 2023.

[H6] Giuseppe Bevacqua, Jonathan Cacace, Alberto Finzi, and Vincenzo Lippiello. Mixed-Initiative Planning and Execution for Multiple Drones in Search and Rescue Missions. *Proceedings of the International Conference on Automated Planning and Scheduling*, 25:315–323, April 2015.

[H7] Adrian Boteanu, David Kent, Anahita Mohseni-Kabir, Charles Rich, and Sonia Chernova. Towards Robot Adaptability in New Situations. 2015.

[H8] Hong Cai and Yasamin Mostofi. When Human Visual Performance Is Imperfect—How to Optimize the Collaboration Between One Human Operator and Multiple Field Robots. In *Trends in Control and Decision-Making for Human-Robot Collaboration Systems*, pages 271–299. February 2017. Journal Abbreviation: Trends in Control and Decision-Making for Human-Robot Collaboration Systems.

[H9] JOSÉ CAÑAS, JOSÉ QUESADA, ADORACIÓN ANTOLÍ, and INMACULADA FAJARDO. Cognitive flexibility and adaptability to environmental changes in dynamic complex problem-solving tasks. *Ergonomics*, 46(5):482–501, April 2003. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/0014013031000061640.

[H10] Jessie YC Chen, Michael J Barnes, and Michelle Harper-Sciarini. Supervisory control of multiple robots: Human-performance issues and user-interface design. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 41(4):435–454, 2010.

[H11] Jacob W. Crandall, Nathan Anderson, Chace Ashcraft, John Grosh, Jonah Henderson, Joshua McClellan, Aadesh Neupane, and Michael A. Goodrich. Human-Swarm Interaction as Shared Control: Achieving Flexible Fault-Tolerant Systems. In Don Harris, editor, *Engineering Psychology and Cognitive Ergonomics: Performance, Emotion and Situation Awareness*, volume 10275, pages 266–284. Springer International Publishing, Cham, 2017. Series Title: Lecture Notes in Computer Science.

[H12] Wei Dai, Yaru Liu, Huimin Lu, Zhiqiang Zheng, and Zongtan Zhou. A shared control framework for human-multirobot foraging with brain-computer interface. *IEEE Robotics and Automation Letters*, 6(4):6305–6312, 2021.

[H13] Yves Georgy Daoud, Kshitij Goel, Nathan Michael, and Wennie Tabib. Collaborative Human-Robot Exploration via Implicit Coordination. In *2022 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, pages 80–86, November 2022. ISSN: 2475-8426.

[H14] Daniel S. Drew. Multi-Agent Systems for Search and Rescue Applications. *Current Robotics Reports*, 2(2):189–200, June 2021.

[H15] Mica R Endsley. Toward a theory of situation awareness in dynamic systems. *Human factors*, 37(1):32–64, 1995.

[H16] Raul Fernandez-Rojas, Anthony Perry, Hemant Singh, Benjamin Campbell, Saber Elsayed, Robert Hunjet, and Hussein A. Abbass. Contextual Awareness in Human-Advanced-Vehicle Systems: A Survey. *IEEE Access*, 7:33304–33328, 2019. Conference Name: IEEE Access.

[H17] Vijay Govindarajan, Subhrajit Bhattacharya, and Vijay Kumar. Human-Robot Collaborative Topological Exploration for Search and Rescue Applications. In Nak-Young Chong and Young-Jo Cho, editors, *Distributed Autonomous Robotic Systems*, Springer Tracts in Advanced Robotics, pages 17–32, Tokyo, 2016. Springer Japan.

[H18] A. Hong, O. Igharoro, Y. Liu, F. Niroui, G. Nejat, and B. Benhabib. Investigating Human-Robot Teams for Learning-Based Semi-autonomous Control in Urban Search and Rescue Environments. *Journal of Intelligent & Robotic Systems*, 94(3):669–686, June 2019.

[H19] Rafal Krzysiak and Sachit Butail. Information-Based Control of Robots in Search-and-Rescue Missions With Human Prior Knowledge. *IEEE Transactions on Human-Machine Systems*, 52(1):52–63, February 2022. Conference Name: IEEE Transactions on Human-Machine Systems.

[H20] Jeong-Seon Lim, Marcella Astrid, Hyun-Jin Yoon, and Seung-Ik Lee. Small Object Detection using Context and Attention. In *2021 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, pages 181–186, Jeju Island, Korea (South), April 2021. IEEE.

[H21] Yen-Chen Liu. Task-space coordination control of bilateral human–swarm systems. *Journal of the Franklin Institute*, 352(1):311–331, 2015.

[H22] Yugang Liu and Goldie Nejat. Multirobot Cooperative Learning for Semiautonomous Control in Urban Search and Rescue Applications. *Journal of Field Robotics*, 33(4):512–536, 2016. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/rob.21597.

[H23] Gunter Lösel. Can robots improvise? *Liminalities*, 14(1):185–206, 2018.

[H24] Robin R Murphy. The 100 100 challenge for computing in rescue robotics. In *2011 IEEE International Symposium on Safety, Security, and Rescue Robotics*, pages 72–75. IEEE, 2011.

[H25] Manuel Müller, Tamás Ruppert, Nasser Jazdi, and Michael Weyrich. Self-improving situation awareness for human–robot-collaboration using intelligent Digital Twin. *Journal of Intelligent Manufacturing*, May 2023.

[H26] Manisha Natarajan, Esmaeil Seraj, Batuhan Altundas, Rohan Paleja, Sean Ye, Letian Chen, Reed Jensen, Kimberlee Chestnut Chang, and Matthew Gombolay. Human-robot teaming: grand challenges. *Current Robotics Reports*, 4(3):81–100, 2023.

[H27] Stefanos Nikolaidis, David Hsu, Yu Xiang Zhu, and Siddhartha Srinivasa. Human-Robot Mutual Adaptation in Shared Autonomy. *Proceedings of the ... ACM SIGCHI. ACM Conference on Human-Robot Interaction*, 2017:294–302, March 2017.

[H28] Sarwar Hussain Paplu, Mohammed Nazrul Islam Arif, and Karsten Berns. Utilizing semantic and contextual information during human-robot interaction. In *2021 IEEE International Conference on Development and Learning (ICDL)*, pages 1–6. IEEE, 2021.

[H29] Vasili Ramanishka, Abir Das, Jianming Zhang, and Kate Saenko. Top-Down Visual Saliency Guided by Captions. pages 7206–7215, 2017.

[H30] Sarvapali D Ramchurn, Joel E Fischer, Yuki Ikuno, Feng Wu, Jack Flann, and Antony Waldock. A study of human-agent collaboration for multi-uav task allocation in dynamic environments. In *Proceedings of the 24th International Joint Conference on Artificial Intelligence (IJCAI)*, pages 1184–1192, 2015.

[H31] Arturo G. Roa-Borbolla, Antonio Marin-Hernandez, Ericka J. Rechy-Ramirez, and Hector Vazquez-Leal. Priority exploration by mobile robots for search and rescue situations. In *2017 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC)*, pages 1–6, Ixtapa, November 2017. IEEE.

[H32] Sumukha Udupa, Vineet R Kamat, and Carol C Menassa. Shared autonomy in assistive mobile robots: a review. *Disability and Rehabilitation: Assistive Technology*, 18(6):827–848, 2023.

[H33] Pierre Urlings, Jeffrey Tweedale, Christos Sioutis, and Nikhil Ichalkaranje. Intelligent Agents and Situation Awareness. In Vasile Palade, Robert J. Howlett, and Lakhmi Jain, editors, *Knowledge-Based Intelligent Information and Engineering Systems*, Lecture Notes in Computer Science, pages 723–733, Berlin, Heidelberg, 2003. Springer.

[H34] Franziska Doris Wolf and Ruth Maria Stock-Homburg. How and When Can Robots Be Team Members? Three Decades of Research on Human–Robot Teams. *Group & Organization Management*, 48(6):1666–1744, December 2023. Publisher: SAGE Publications Inc.

[H35] Fereshta Yazdani, Benjamin Brieber, and Michael Beetz. Cognition-Enabled Robot Control for Mixed Human-Robot Rescue Teams. In Emanuele Menegatti, Nathan Michael, Karsten Berns, and Hiroaki Yamaguchi, editors, *Intelligent Autonomous Systems 13*, Advances in Intelligent Systems and Computing, pages 1357–1369, Cham, 2016. Springer International Publishing.

Chapter 5

Conclusion

In this chapter a combined summary of the above chapters is created and the main research questions from chapter 1 are answered in section 5.1. An graph of the explored topics and how they are interlinked is also created in figure 5.1. Further, a proposed approach for the thesis including the primary research question and preliminary problem statement is given in section 5.2. A tentative timeline for the thesis is given in section 5.2.

5.1 Research questions: Literature study

1. *What are the state-of-the-art planning methods and baseline techniques for target search and volumetric exploration using Micro Aerial Vehicles (MAVs)?*

   State-of-the-art exploration planning strategies integrate frontier and sampling-based methods to obtain the greatest value. While most research focuses on incremental improvements to viewpoint utility functions, notable works such as [A60], [A27], and [A19] stand out for their novelty and robust experimental evaluations. These works serve as promising baselines, offering valuable insights for code development and reuse. The review in section 2.3 also highlights key techniques that make the problem tractable in real-time for aerial vehicles. Research in target exploration predominantly focuses on structured indoor settings and limited attention is given to extreme settings like SAR owing to their higher complexity. This complexity can be simplified by using semantic classes as representations for the environment's features, facilitating mutual understanding between humans and robots. An appropriate formulation for these **semantic representations and relationships** in emergency response scenarios is seen as a first potential gap to explore in the thesis. Additionally, **combining semantics with visual attention** holds the promise of providing a human-like navigation for finding objects of interest, which is a hypothesis that will be further validated in the thesis. Ultimately, the recommendation here would be to explore an approach that seamlessly integrates metric features, such as an occupancy grid, with semantic features to drive search to visually attentive regions of space [A23] [A55]. This integrated approach could enable

simultaneous exploration and visual search using **combinatorial planning** methods [A60].

2. *What methods exist in literature for coordinating the actions of multiple robots engaged in target exploration in an unstructured cluttered environment?*

   In the context of planning for exploration, coordination can be seen as a redistribution of tasks among multiple robots such that costs like time or overlapping area is minimized. Among the many techniques in literature, **iterative optimization** techniques like auction based methods or pairwise partitioning stand out. These approaches allow decentralisation of the system and increase reliability, both of which might be critical in uncertain communication environments for exploration. A key recommendation here is to explore the actual **data structure** that is exchanged among multiple robots which is relevant to semantically informed target search. For instance, this could be confidence scores of the same object detected from multiple viewpoints (increases detection accuracy) or semantic labels of different objects that are closely related to each other (decreases time-to-search).

3. *How and when should a human be included in a multi-robot system for enhancing the quality of the target search task?*

   Humans can team up with robots on various levels of abstraction. The review in chapter 4 suggests that to balance workload but still share parts of decision making, humans can be incorporated in the problem at a task-level – providing high level guidance or setting priorities. This can be done offline where the human can set **prior context** and define situational variables to make the robot's task easier, or it can be in the form of online interventions where the human can dynamically adjust **priorities of objects**. The challenge in this sub-problem is to create appropriate representations of features in the environment such that a human language (priorities) can be translated to robot language (information gain) while still keeping robot actions explainable. A recommendation would be use techniques that can create these **translations** such as concept graphs [A26], concept maps [A29], and language-visual models [A29] [A58].

5.2 Proposed approach: Thesis

Primary research statement

Design an algorithm which can generate a plan for a MAV in a cluttered unfamiliar environment to quickly locate objects of interest.

Sub-questions

- What representations of the environment's features are essential to capture priorities of targets using semantic relationships as priors?

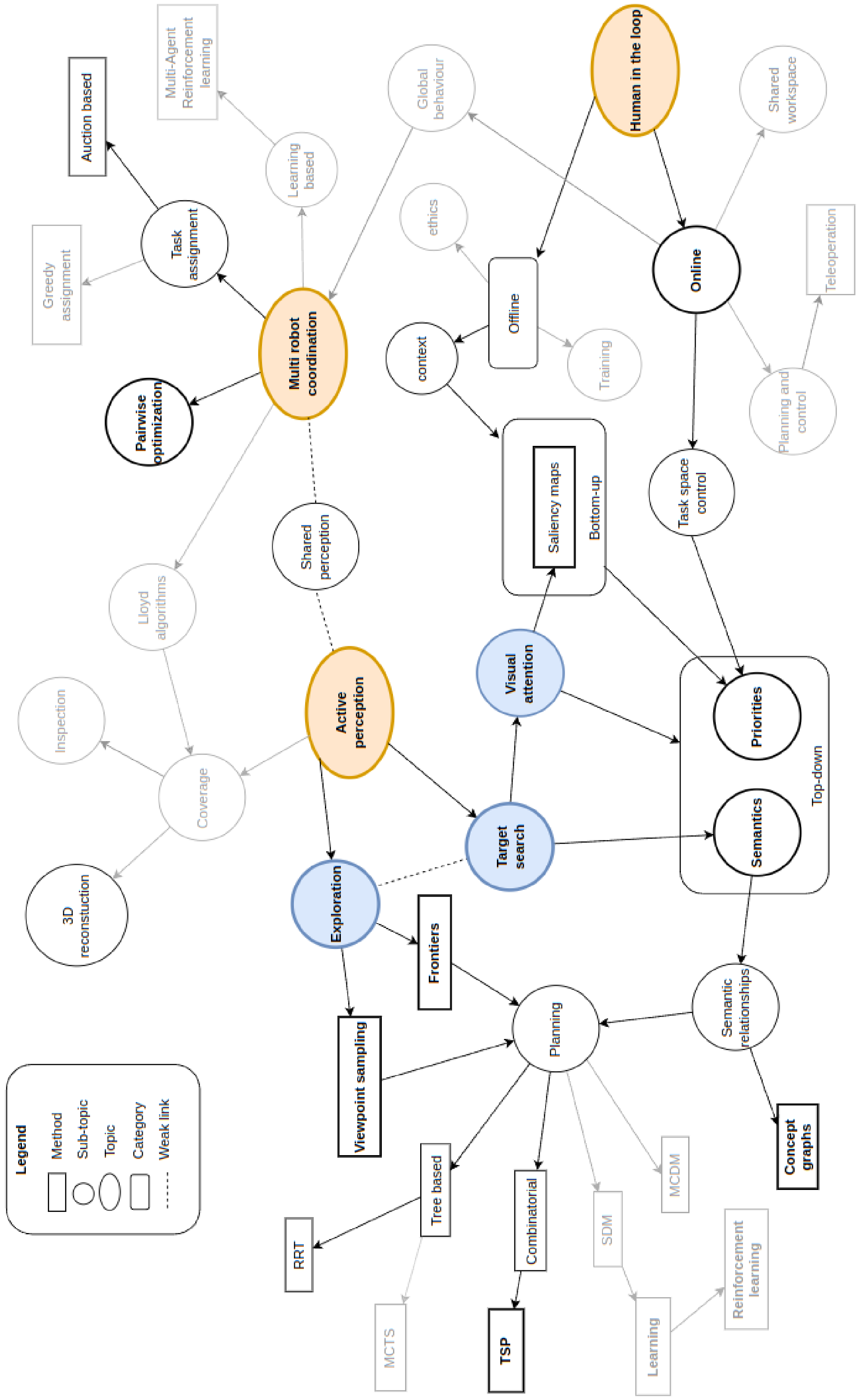

Figure 5.1: Topic graph. Darker lines mean more relevant topics

- How can these representations be incorporated with existing 3D exploration planners to quickly search for targets using combinatorial planning methods like TSPs?
- How can such a system be deployed on a real drone with hardware constraints like sensor limitations and computational budgets?

Problem formulation

To formalise the primary question, a core problem formulation related to the active perception research question is created. This core problem will be the central theme of the thesis and human guidance or multi-robot coordination will be added to it in an ad-hoc manner.

The problem considered in this work is of exploring a bounded volume $\mathcal{V} \subset \mathbb{R}^3$ and simultaneously looking for N^t target objects of interest (*OOIs*) $\mathbb{O}_c \subset \mathbb{O}$ in an unknown environment. Here, $\mathbb{O}$ is the set of all possible objects that can be encountered in the scenario (fig. 5.2 (left)). An autonomous aerial robot is used to perform this task, where $\mathbf{x}_t \in \mathcal{V}$ is the robot's pose in $SO(3)$ at time instant t. The action space of the robot is $(x, y, z, \psi) : \mathbb{R}^3 \times \mathcal{S}^1$ assuming differentiable flat control [A40].

Environment features: The features of the 3D environment are represented using metric and semantic spaces. At each time step t the robot with 3D sensor model H receives a new local observation $z_t = H(\mathbf{x}_t)$ which is used to update *a)* a global probabilistic occupancy map $\mathcal{M}$, and *b)* a set $\mathbb{O}_t$ of segmented objects represented as semantic classes. It is assumed that the sets $\mathbb{O}_t$ and $\mathbb{O}_c$ have a semantic relationships defined by function $r : \mathbb{O}_t \times \mathbb{O} \rightarrow \mathbb{R}$ that returns priorities of objects as scalars and can be exploited to guide the robot to regions biased towards the target *OOIs* (fig. 5.2 (right)). Such relations can be created via concept graphs [A26] (fig. 4.1), concept maps [A29] or even learnt from human input overtime. A target object $o_c \in \mathbb{O}_c$ is considered discovered when it is detected in the current view i.e. $o_c \in \mathbb{O}_t$.

Problem statement: Given a set of target objects of interest $\mathbb{O}_c$, a semantic relationship function r, and the robot's initial configuration $\mathbf{x}_0$, use z_t to populate $\mathcal{M}$ and $\mathbb{O}_t$, and find a prioritised collision free path σ through $\mathcal{V}$ such that all objects $\mathbb{O}_c \cap \mathbb{O}$ are discovered in minimum time. Figure 5.2 shows a graphical representation of the problem statement.

Timeline

A rough timeline is shown in figure 5.3. The tasks under the simulation category will be broken up into the following sub goals:

1. Incorporate custom volumetric environment representations into an existing 3D exploration planner [M32]. Start with ground truth data to start and integrate with step 3 later.
2. Use graph based methods to sample viewpoints around objects and create utility functions to rank viewpoints [A4] [A60] [A21]. At this stage it might also be helpful to start testing a naive TSP method based on waiting times to visit the viewpoints.

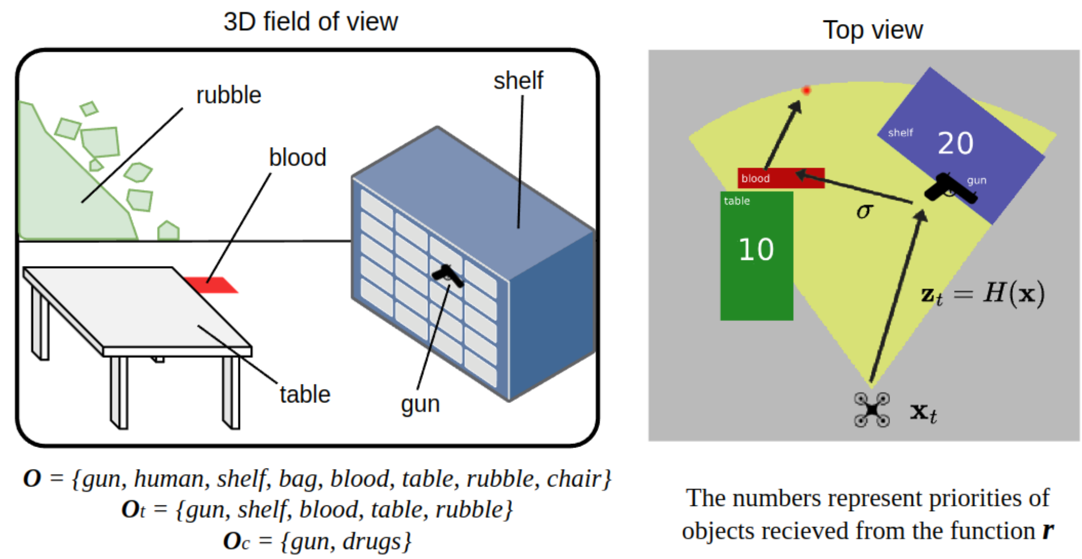

Figure 5.2: Problem formulation. Left: Perception at time t. Right: Collision free path σ which respects priorities.

3. Create ground truth relationship graphs and integrate a semantic segmentation pipeline with RGBD cameras. At this stage experimental testing will also guide the choice of methods.

4. Integrate semantic graphs, environment representations and TSP tours to gather statistics of the method in simulation before proceeding to evaluate method in real life.

An important goal for the thesis is to deploy algorithms on real-drones and not just in simulation. This means setting up hardware experiments parallel to simulation and managing expectations for both simultaneously. At the time of writing this literature study, the work from [M32] has been implemented and tuned for autonomous exploration in a cluttered obstacle rich environment (fig. 5.4).

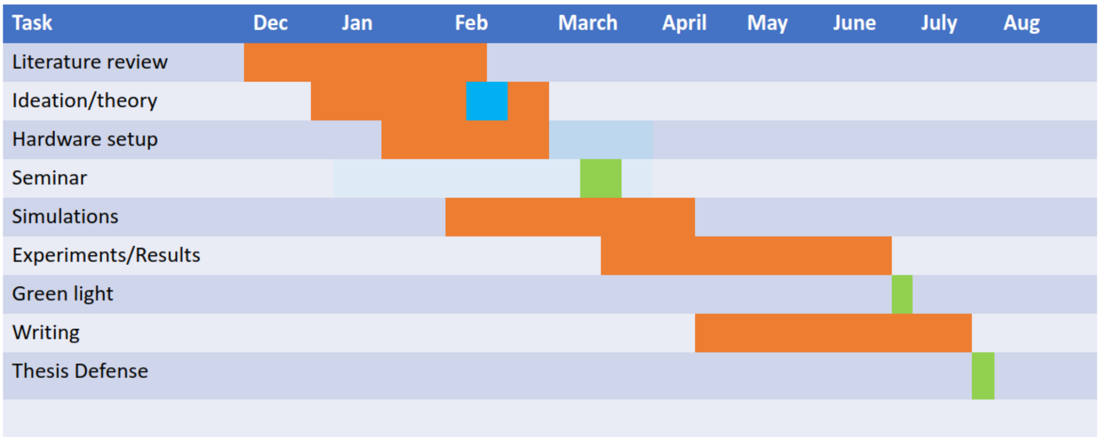

Figure 5.3: Thesis timeline

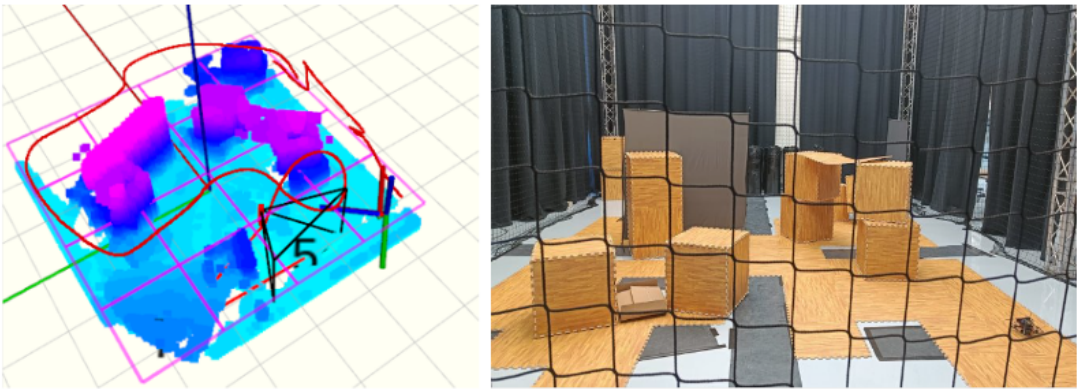

Figure 5.4: Hardware setup progress