

Find Everything: A General Vision Language Model Approach to Multi-Object Search

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Abstract — Efficient navigation and search in unknown environments for multiple objects is a fundamental challenge in robotics, particularly in applications such as warehouse management, domestic assistance, and search-and-rescue. The Multi-Object Search (MOS) problem involves navigating to a sequence of locations to maximize the likelihood of finding target objects while minimizing travel costs. In this paper, we introduce a novel approach to the MOS problem, called Finder, which leverages vision language models (VLMs) to locate multiple objects across diverse environments. Specifically, our approach introduces multi-channel score maps to track and reason multiple objects simultaneously during navigation, along with a score fusion technique that combines scene-level and object-level semantic correlations. We validate our approach through extensive experiments in both simulated and real-world environments. The results demonstrate that Finder outperforms existing multi-object search methods using deep reinforcement learning and VLM. Additional ablation and scalability studies highlight the importance of our design choices and show the system’s robustness with increasing number of target objects. Website: <https://find-all-my-things.github.io/>

I. INTRODUCTION

In various real-world applications, robots need to efficiently identify and locate multiple objects to complete tasks. This is critical in domains such as warehouse management [1], construction inspection [2], and domestic [3], and retail assistance [4], [5]. This challenge is addressed by multi-object search (MOS) [6] which describes the problem of finding multiple target objects in an unknown environment, while minimizing the robot’s travel distance and search time [7].

Existing MOS methods can be categorized into: 1) probabilistic planning [6], [8]–[10], and 2) deep reinforcement learning (DRL) methods [7], [11]–[17]. Probabilistic planning methods address uncertainty in object locations using Partially Observable Markov Decision Processes (POMDPs) to estimate belief states and plan robot actions under partial observability, while DRL methods train robots to explore environments by optimizing action selection using a reward function [18]. However, these methods are limited by: 1) inefficient exploration due to a lack of direct semantic modeling between target objects and the scene [15], and 2) poor generalizability due to the sim-to-real gap [16].

Recently, large foundation models [19], such as vision-language models (VLMs), and large language models (LLMs), have demonstrated strong common-sense knowledge and reasoning abilities. These models can address the limitations

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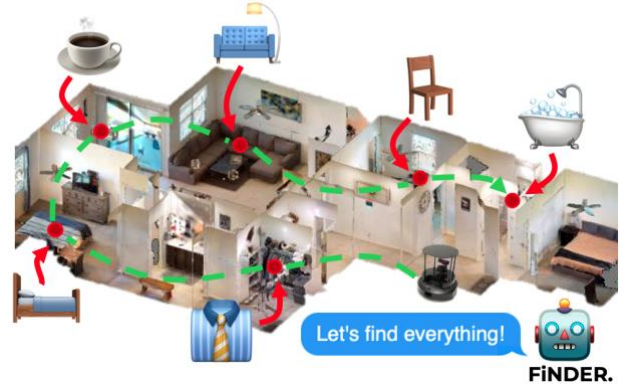


Fig. 1. Finder utilizes a vision language model to address the multi-object search problem for a mobile robot in any indoor environment.

of existing MOS methods by explicitly modeling the semantic correlation between target objects and the environment, while also generalizing across environments. As a result, these models have been applied to single object search (SOS) tasks using either: 1) VLMs (e.g., CLIP, BLIP, etc.) to generate scene-level embeddings that capture the semantic correlations between the robot’s environment, and the target object [16], [20]–[23], to guide the robot towards regions with high target object likelihood; or, 2) VLMs/LLMs to generate scene captions that describe both the spatial layout and semantic details of the robot’s environment [24]–[30], which are then used to plan the robot’s actions. However, these SOS methods have limitations: 1) they cannot be directly applied to MOS, as they lack explicit mechanisms to track and reason about multiple objects simultaneously, and 2) scene-level embeddings are often noisy and coarse [31], which cannot be effectively applied in object-dense environments. In such cases, fine-grained, object-level embeddings are needed.

In this paper, we introduce Finder, the first MOS approach that leverages VLMs to locate multiple target objects in various unknown environments, Fig. 1. Our key contributions are: 1) we introduce multi-channel score maps to simultaneously capture and track the semantic correlation between multiple target objects, the environment, and objects within the environment, 2) we develop a score map fusion technique that combines scene-level correlations between the scene and target objects, with object-level correlations between the scene objects and target objects, to overcome the limitations of coarse scene-level embeddings, and 3) we conducted extensive simulation and real world experiments to validate Finder’s performance. We make our code available upon request on our website to encourage reproducibility and further research in this area.

II. RELATED WORKS

Current object search methods for mobile robots can be categorized into: 1) probabilistic planning methods for MOS [6], [8]–[10] 2) DRL methods for MOS [7], [11]–[17], and 3) VLM methods for SOS [20]–[30], [32], [33].

A. Probabilistic Planning Methods (PP) for MOS

Probabilistic planning methods for MOS account for uncertainty in object locations and robot perception by using probabilistic frameworks to estimate belief states and plan actions under partial observability [6]. These methods generally assumed no prior knowledge of object locations, requiring the robot to iteratively update its belief using noisy sensor data. POMDPs are commonly used to address the uncertainty and partial observability in MOS. Usages of POMDPs included: 1) structuring the belief space based on objects and object classes for belief updates across multiple objects [6], 2) using point clouds to construct a occupancy octree for occlusion-aware searches and continuous belief updates [8], 3) managing dynamic environments through belief tree reuses [9], and 4) reducing computational complexity by segmenting the search areas into regions [10]. Simulated experiments were conducted in 2D grid worlds [6], [10], and 3D indoor environments [8], [9]. Real-world experiments were conducted in indoor environments using robots such as Spot and Kinova MOVO [6], [8].

B. Deep Reinforcement Learning Methods (DRL) for MOS

In DRL methods for MOS, the robot is trained to explore unknown environments and locate multiple objects by repeatedly interacting with the environment during offline training [7]. These methods used DRL frameworks such as Deep Q Networks (DQN) [11], Proximal Policy Optimization (PPO) [7], [12]–[15], [17], or hybrid approaches that combine classical SLAM with learned policies [16], to optimize the robot’s navigation action selection based on RGB-D inputs [7], [12]–[17], LiDAR [16], or graph-based data [11]. The outputs of the DRL policies included: 1) discrete navigation actions (e.g., go straight, turn right, etc.) [7], [11], [13]–[15], [17], 2) continuous navigation actions [12], or 3) navigation waypoints [16]. DRL methods were primarily evaluated in simulation environments using Matterport3D [7], [13]–[16], custom-built environments [11], Gibson [14]–[16] and iGibson [12], [17]. Some methods were validated on physical robots, such as LoCoBot [12], [16] or Toyota HSR [12], [17]

C. Large Foundation Model Methods (LFM) for SOS

LFM methods for SOS focus on enabling robots to navigate unknown environments by leveraging natural language descriptions and visual inputs [23]. These methods incorporate VLMs and LLMs to guide object search using semantic reasoning and multi-modal robot perception [30]. Namely, these methods utilize RGB [21], [22], [25], [26], [33] or RGB-D [20], [23], [24], [27]–[30], [32] images from egocentric robot perspectives, to detect target objects using open-vocabulary models (e.g., GroundingDINO [34], SAM [35]), followed by planning discrete actions such as moving forward or turning. The models used pre-trained VLMs such as CLIP [20], [21], [30], [33], GLIP [24], [25] Llama-Adapter

[26], BLIP [22], [23], [28] as well as LLMs such as, GPT-4 [26], GPT-4V [29] [30], DeBERTa [24], RoBERTa [27] for navigation reasoning and instruction parsing. Experiments were conducted in simulated environments such as Habitat [20], [29], [32] RoboTHOR [20], [24], [25], PASTURE [20], [21], [23], [24] HM3D [21]–[24], [26]–[28], [30] HSSD [28], Gibson [21], [23], [27] ProcTHOR-10k [29], [33], were commonly used to test performance in indoor settings. Experiments with real-world hardware, including LoCoBot [20] [32], iRobot [26], Turtlebots [25], [29], [30], Jackal [27], and Spot [23], further validated the proposed approaches in real-world scenarios.

D. Summary of Limitations

Probabilistic planning methods face computational inefficiency in scaling to large, complex environments due to the need to maintain and update belief states for multiple objects over extended planning horizons [6]. DRL methods are limited by 1) inefficient exploration, as they optimize navigation based solely on sensory inputs without directly modeling semantic correlations between target objects and the scene [14], and 2) poor generalizability, requiring extensive training data and resources that hinder transferring learned policies from simulation to real-world scenarios [16], [36]

While LFM methods can generalize well in a zero-shot manner, they are limited by: 1) their focus on SOS, making them unable to track multiple objects simultaneously for MOS where objects may be semantically related [23], and 2) reliance on coarse embeddings obtained from LFM that capture only scene-level correlation between target objects and the environment, missing fine-grained correlations between target objects with objects in the scene [20], [29].

To address these limitations, we propose Finder, the first VLM-based approach that introduces multi-channel maps to address the challenges of tracking multiple objects simultaneously for MOS, and a score fusion technique to capture both scene and object-level correlations.

III. THE MULTI-OBJECT SEARCH PROBLEM FORMULATION

The MOS problem requires a mobile robot to search for a list of objects in an unknown environment. The robot is equipped with an RGB-D camera and has a state $\mathbf{x}_r(t) \in \mathbb{R}^N$ at time t , where $\mathbf{x}_r(t) = (x, y, z, \phi)$ represents its position and orientation. The environment consists of L static scene objects $\mathcal{O}_{\text{sne}} = \{o_{s_1}, o_{s_2}, \dots, o_{s_L}\}$. The set of K static target objects to be located is denoted by $\mathcal{O}_{\text{tgt}} = \{o_{t_1}, o_{t_2}, \dots, o_{t_K}\}$, $\mathcal{O}_{\text{tgt}} \subseteq \mathcal{O}_{\text{sne}}$, where each object o_{t_j} occupies an unknown position \mathbf{x}_{t_j} . The objective of the MOS problem is to minimize the cumulative distance travelled d required for the robot to locate all objects in \mathcal{O}_{tgt} given control inputs $u(t)$:

$$\min_{u(t)} d = \int_0^T \|\dot{\mathbf{x}}_r(t)\| dt, \quad (1)$$

where T is the total time to complete the search.

IV. THE FINDER ARCHITECTURE

The proposed multi-object search architecture, Finder, is presented in Fig. 2. The goal is for the robot to find multiple

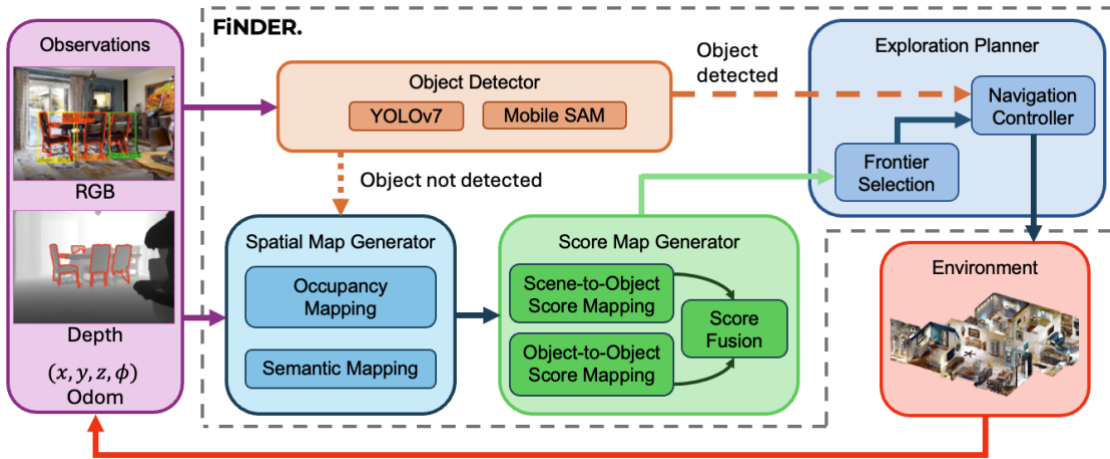


Fig. 2. The proposed Finder architecture consists of four modules: 1) *Object Detector* which identifies whether a scene/target object is present in the scene, 2) *Spatial Map Generator* which generates an occupancy and semantic map for navigation, 3) *Score Map Generator* which generates a unified score map representing the combined scene-to-object score map and object-to-object score map, and 4) *Exploration Planner* which selects the next frontier or target waypoint to navigate towards.

target objects in an unknown environment by exploring areas with the highest semantic correlation scores. These scores are based on the scene-level correlation between the target objects and the scene as well as object-level correlations between the scene objects and target objects. This allows the robot to explore regions that are semantically correlated with the target objects. The architecture consists of four main modules: 1) *Object Detector*, 2) *Spatial Map Generator*, 3) *Score Map Generator*, and 4) *Exploration Planner*.

A. Object Detector

The *Object Detector* module identifies whether a scene object or a target object is in the robot view from an RGB image I_{RGB}^t and depth image I_D^t at time t . Specifically, YOLOv7 [37] is used to output class labels c_i (within the COCO [38] classes) and bounding boxes b_i from I_{RGB}^t , [39]. Segmentation masks S^t are generated using Mobile-SAM [35] from the RGB image I_{RGB}^t and bounding boxes b_i . If a target object o_{t_j} is detected, the closest point on the target relative to the robot is identified from I_D^t and S^t . The closest point p_i is then projected into 3D space using the pinhole camera model [40], [41], to obtain a target object waypoint w_{t_i} , which is passed to the *Navigation Controller* within the *Exploration Planner*. If a target object is not detected, the masks S^t are passed into the *Spatial Map Generator* module.

B. Spatial Map Generator

The *Spatial Map Generator* module generates metric maps of the environment using two sub-modules: 1) the *Occupancy Mapping*, and 2) *Semantic Mapping*. The *Occupancy Mapping* sub-module generates an occupancy map $M_o^t \in \mathbb{R}^{H \times W}$ from depth image I_D^t and odometry information ρ^t at time t , updating as the robot navigates in the environment. Obstacles are identified by converting I_D^t into a point cloud P^t , and projecting these points onto the occupancy map M_o^t . The *Semantic Mapping* module generates a semantic map $M_s^t \in \mathbb{R}^{H \times W}$ from the RGB and depth images I_{RGB}^t and I_D^t , respectively. Specifically, the segmentation mask S^t for each

detected object are projected onto a 2D map using the semantic mapping procedure in [42].

C. Score Map Generator

We introduce the *Score Map Generator* module, consisting of two sub-modules: 1) the *Scene-to-Object (StO) Score Mapping*, 2) the *Object-to-Object (OtO) Score Mapping*, and 3) *Score Fusion*. The *StO Score Mapping* generates scene-level correlation scores to capture the semantic relationships between target objects and the scene. The *OtO Score Mapping* generates object-level correlation scores to capture the relationships between target objects and scene objects.

1) Scene to Object Score Mapping

The *StO Mapping* module generates a score map where each element represents the semantic correlation of a specific location with respect to each of the target objects, Fig. 3. Specifically, it takes as inputs I_{RGB}^t and outputs a multi-channel *StO* score map $V_{S \rightarrow o_{tgt}}^t \in \mathbb{R}^{K \times H \times W}$ of the same spatial dimension as the occupancy map. The scene embedding $e_s^t \in \mathbb{R}^D$ is obtained by applying BLIP2 [43], a VLM, to I_{RGB}^t :

$$e_s^t = \text{VLM}(I_{RGB}^t). \quad (2)$$

Similarly, for each target object o_{t_j} , target embeddings $e_{t_j} \in \mathbb{R}^D$ are obtained by applying BLIP2 to the text prompt p_{t_j} representing the object's name:

$$e_{t_j} = \text{VLM}(p_{t_j}), \forall o_{t_j} \in O_{tgt}. \quad (3)$$

The semantic correlation $S(e_s^t, e_{t_j})$ between the scene I_{RGB}^t and each target object o_{t_j} is computed by the cosine similarity. We follow [23] by generating a cone-shaped confidence mask $C^t \in \mathbb{R}^{H \times W}$ at each time step to represent the camera's field of view (FOV). The confidence of each pixel is maximal at the optical axis with a value of 1 and decreases away from the optical axis based on $\cos^2(\theta / (\theta_{FOV}/2) * \pi/2)$. Pixels representing obstacles, identified from I_D^t , are assigned a value of 0 in C^t . Each channel in the scene-level score map $V_{S \rightarrow o_{tgt}}^t$, namely $V_{S \rightarrow o_{t_j}}^t \in \mathbb{R}^{1 \times H \times W}$,

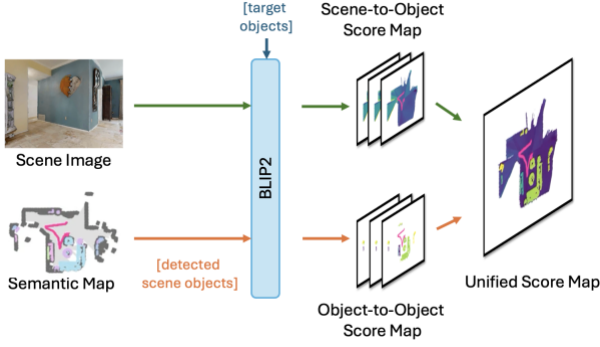


Fig. 3. Overview of the Unified Score Map generation process.

corresponds to the score map for object o_{t_j} , and can be obtained by scaling \mathbf{C}^t with $S(\mathbf{e}_{s_i}^t, \mathbf{e}_{t_j}^t)$:

$$\mathbf{V}_{s \rightarrow o_{t_j}}^t = \mathbf{C}^t \cdot S(\mathbf{e}_{s_i}^t, \mathbf{e}_{t_j}^t), \forall o_{t_j} \in \mathcal{O}_{\text{tgt}}. \quad (4)$$

It is updated based on a weighted average of the current and previous values [23]:

$$\mathbf{V}_{s \rightarrow o_{t_j}}^t = \frac{\mathbf{C}^t \odot \mathbf{V}_{s \rightarrow o_{t_j}}^t + \mathbf{C}^{t-1} \odot \mathbf{V}_{s \rightarrow o_{t_j}}^{t-1}}{\mathbf{C}^t + \mathbf{C}^{t-1}}, \forall o_{t_j} \in \mathcal{O}_{\text{tgt}}, \quad (5)$$

where \odot is the Hadamard product. Similarly, the confidence map \mathbf{C}^t is updated as follows [23]:

$$\mathbf{C}^t = \frac{(\mathbf{C}^t)^2 + (\mathbf{C}^{t-1})^2}{\mathbf{C}^t + \mathbf{C}^{t-1}}. \quad (6)$$

2) Object to Object Score Mapping

The *OtO Score Mapping* module generates a score map representing fine-grained, object-level correlations between target objects and scene objects, Fig. 3. Each element in the score map represents the cooccurrence score of a specific location in the scene. Specifically, a higher score represents the presence of scene objects that commonly appear with the target objects. It takes as inputs \mathbf{I}_{RGB}^t and outputs a multi-channel scene object to target object score map $\mathbf{V}_{o_{\text{sne}} \rightarrow o_{\text{tgt}}}^t \in \mathbb{R}^{K \times H \times W}$ of the same spatial dimension as \mathbf{M}_o^t .

We compute a cooccurrence matrix $\mathbf{W} \in \mathbb{R}^{L \times K}$ where $w_{ij} = S(\mathbf{e}_{s_i}, \mathbf{e}_{t_j}) \in \mathbf{W}$ represents the cosine similarity between the embeddings of the scene object o_{s_i} and target object o_{t_j} . These embeddings are computed from Eq. 3. For each target object o_{t_j} , the corresponding channel of the score map $\mathbf{V}_{o_{\text{sne}} \rightarrow o_{t_j}}^t$ is computed by weighting each channel i of the semantic map, $\mathbf{M}_{s, o_{s_i}}^t$, representing the presence of a scene object o_{s_i} , with the cosine similarity $S(\mathbf{e}_{s_i}, \mathbf{e}_{t_j})$. This scales the contribution of each scene object by how semantically correlated it is to the target object. The OtO score map for each target object o_{t_j} at each time step t is then given by:

$$\mathbf{V}_{o_{\text{sne}} \rightarrow o_{t_j}}^t = \sum_{o_{\text{sne}}} \mathbf{M}_{s, o_{s_i}}^t S(\mathbf{e}_{s_i}, \mathbf{e}_{t_j}), \forall o_{t_j} \in \mathcal{O}_{\text{tgt}}. \quad (7)$$

3) Score Fusion

The *Score Fusion* module introduces a score fusion technique that combines both scene- and object-level correlations into a unified score map to guide the robot towards regions of high target object likelihood. Specifically, it combines the multi-channel StO score map $\mathbf{V}_{s \rightarrow o_{t_j}}^t$ and OtO score map $\mathbf{V}_{o_{\text{sne}} \rightarrow o_{t_j}}^t$. Specifically, the unified score map

$\mathbf{V}_{s, o_{\text{sne}} \rightarrow o_{\text{tgt}}}^t \in \mathbb{R}^{H \times W}$ is obtained by element-wise addition of $\mathbf{V}_{s \rightarrow o_{t_j}}^t$ and $\mathbf{V}_{o_{\text{sne}} \rightarrow o_{t_j}}^t$, and then summing over the channels to obtain a combined score:

$$\mathbf{V}_{s, o_{\text{sne}} \rightarrow o_{\text{tgt}}}^t = \sum_{o_{\text{tgt}}} \mathbf{V}_{s \rightarrow o_{t_j}}^t + \mathbf{V}_{o_{\text{sne}} \rightarrow o_{t_j}}^t. \quad (8)$$

Therefore, locations on the unified score map, Fig. 3, that are semantically relevant to multiple targets objects, and/or locations with scene objects that are semantically relevant to multiple target objects, will accumulate higher scores.

D. Exploration Planner

The *Exploration Planner* selects the next frontier \mathbf{g} or target object waypoint \mathbf{w}_{t_i} to navigate towards. It comprises two sub-modules: 1) *Frontier Selection*, and 2) *Navigation Controller*. If no target is detected, the *Frontier Selection* sub-module determines the next frontier \mathbf{g} to explore. If a target object o_{t_i} is detected by the *Object Detection* sub-module, then the *Navigation Controller* directly receives the target waypoint \mathbf{w}_{t_i} and navigates towards it. When the distance between the robot and the detected target object is within a threshold ϵ , the target object is found, e.g., o_{t_j} , the object is removed from the search list \mathcal{O}_{tgt} , e.g., $\mathcal{O}_{\text{tgt}} = \mathcal{O}_{\text{tgt}} \setminus \{o_{t_j}\}$. When the search list is empty, the robot triggers “stop” action.

1) Frontier Selection

The *Frontier Selection* sub-module selects the next frontier $\mathbf{g}(x, y)$ for the robot to explore using a utility function that takes as input the occupancy map \mathbf{M}_o^t and unified score map $\mathbf{V}_{s, o_{\text{sne}} \rightarrow o_{\text{tgt}}}^t$. Frontier points are defined as the midpoint at each boundary separating the explored and unexplored areas [44]. Specifically, the goal is to select the frontier \mathbf{g} with the highest utility $U(\mathbf{g})$, which is based on: 1) the score $s(\mathbf{g})$, calculated from $\mathbf{V}_{s, o_{\text{sne}} \rightarrow o_{\text{tgt}}}^t$ as the mean score within a fixed radius around each frontier; and 2) the distance to each frontier $d(\mathbf{g})$. Thus, the total utility $U(\mathbf{g})$ for each frontier is given by:

$$U(\mathbf{g}) = \alpha \cdot s + \beta \cdot d. \quad (9)$$

The frontier \mathbf{g} with the highest utility score is passed into the *Navigation Controller*.

2) Navigation Controller

The *Navigation Controller* sub-module generates robot control actions u using either the target object waypoint \mathbf{w}_{t_i} from the *Target Object Detection* sub-module, or the frontier \mathbf{g} from the *Frontier Selection* sub-module. We used a point goal navigation policy Variable Experience Rollout (VER) [45] pretrained in [23]. Robot actions include “move forward”, “turn left”, “turn right”, and “stop”.

V. EXPERIMENTS

We conducted four sets of experiments to evaluate the overall performance of Finder on the MOS task: 1) a comparison study against state-of-the-art (SOTA) methods in simulated building environments, 2) an ablation study to investigate the impact of StO and OtO score map on multi-object search efficiency, 3) a scalability study to evaluate the impact of increasing the number of search targets on

exploration time, and 4) a sim-to-real study in an indoor multi-area building environment to evaluate the generalizability of Finder to real-world environments.

A. Simulation Comparison Study

We compared Finder against SOTA methods using the Habitat simulator [46] on two datasets consisting of high-resolution 3D scans from real-world buildings: HM3D [47], and MP3D [48]. For both HM3D and MP3D datasets, we ran 1000 episodes per method. At the beginning of each episode, the robot was spawned at a random location inside the environment and given a list of 3 target objects. An episode terminated if the robot triggered “stop” or the total number of time steps exceeded 500.

1) *Procedure*: We used two performance metrics for these experiments: 1) success rate (SR) to measure the percentage of successful episodes where the robot found all target objects, and 2) multi-object success weighted by normalized inverse path length (MSPL), based on SPL [49], which measures multi-object search efficiency. MSPL is calculated by:

$$\text{MSPL} = \frac{1}{N} \sum_{i=1}^N S_i \frac{\ell_i}{\max(p_i, \ell_i)}, \quad (10)$$

where N denotes the number of episodes, S_i is a binary indicator of success of episode i , ℓ_i denotes the optimal shortest path length from the start location to all target objects, and p_i denotes the actual robot path length.

2) *Comparison Methods*: We compared against the following three sets of methods: DRL, VLM, and Lower and Upper Bounds.

a) DRL method

In terms of DRL methods, we evaluated our approach against a seminal work in MOS.

Multi-Object Navigation (MultiON) [7]: MultiON uses RGB-D images, a goal vector, and a metric map as inputs. The model uses a ConvNet to process visual inputs and a GRU [50] to maintain memory of the robot’s state for action generation.

b) VLM methods

In terms of VLM methods, we compared Finder against four methods that use visual or language embeddings to guide the search process. The following methods were selected as they used the same sensor input as ours, are open sourced, and widely recognized in the research community. These methods were originally designed for SOS, we adapted them for MOS by searching for the target object from \mathcal{O}_{tgt} sequentially.

CLIP on Wheels (CoW) [20]: CoW constructs a metric map from RGB-D images for frontier exploration and uses CLIP to localize the target object.

Leveraging Large Language Models for Visual Target Navigation (L3MVN Zero-Shot) [27]: L3MVN (Zero-Shot) builds a semantic map from RGB-D inputs and uses LLMs to score frontiers from the semantic map for waypoint selection. **L3MVN (Feed-Forward)** [27]: L3MVN (Feed-Forward) uses a feed-forward network to predict frontiers from the semantic map based on LLM embeddings.

Vision-Language Frontier Maps (VLFM) [23]: VLFM generates a value map based on the cosine similarity between the RGB observation and the target object for frontier selection.

TABLE I
COMPARISON BETWEEN FINDER AND SOTA METHODS

Methods	HM3D		MP3D	
	SR↑	MSPL↑	SR↑	MSPL↑
Random Walk	0.5%	0.0043	0.0%	0.0
MultiON	-	-	23.9%	0.159
CoW	14.2%	0.113	1.9%	0.059
L3MVN (Zero-Shot)	27.2%	0.187	6.6%	0.043
L3MVN (Feed-Forward)	28.1%	0.188	7.3%	0.051
VLFM	32.4%	0.155	12.6%	0.104
Oracle	100.0%	1.0	100.0%	1.0
Finder (ours)	63.4%	0.389	55.4%	0.344

c) Lower and upper bound methods

We compared against a lower and upper bound approach to evaluate Finder’s performance in relation to baseline and optimal strategies.

Random Walk: The robot randomly selects a navigation action at each timestep. It serves as the lower bound approach.

Oracle: Oracle plans an optimal shortest path to all the target objects given access to the ground-truth of the object locations and the map. It serves as an upper bound approach.

3) *Results*: The results of comparison study are presented in Table I. Finder outperformed Random Walk, MultiON, CoW, L3MVN, VLFM in terms of SR and MSPL on both HM3D and MP3D datasets. Finder achieved higher SR and MSPL than CoW because CoW only used VLMs to localize the target object. Specifically, CoW did not incorporate reasoning about frontier selection based on the semantic relationship between the scene and the target, leading to less efficient object searches. Similarly, Finder outperformed L3MVN by integrating visual observations and generating a unified score map, while L3MVN relied solely on language semantic priors. In comparison to VLFM, Finder’s higher performance is attributed to its consideration of both scene-level and object-level correlations between the environment and the target object. On the MP3D dataset, Finder also outperformed MultiON, which used predefined cylinders as target objects, disregarding semantic relationships with the robot’s environment. Finder achieved lower SR and MSPL in the MP3D dataset compared to the HM3D dataset because part of the scenes in the MP3D dataset are larger indoor environments. They require longer travel time for all target objects to be found, resulting in lower SR and MSPL given the same amount of maximum timesteps in each episode.

B. Simulation Ablation Study

We conducted an ablation study to investigate the impact of the different score maps used in Finder on multi-object search performance. Namely, we considered the following two variants: **1) Finder w/o Scene-to-Object score map**: This variant does not include StO score map for frontier selection; and **2) Finder w/o Object-to-Object score map**: This variant does not include OtO score map for frontier selection. We conducted 1000 episodes per method using the HM3D dataset, following the procedure in Section V. A.

TABLE II
ABLATION STUDY

	SR \uparrow	MSPL \uparrow
Finder w/o StO	61.5%	0.364
Finder w/o OtO	58.3%	0.337
Finder (ours)	63.4%	0.389

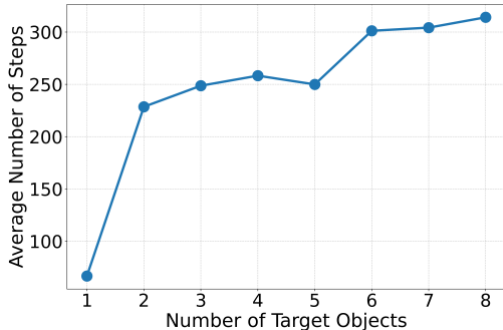


Fig. 4. Average exploration time for increasing number of target objects.

1) *Results*: The ablation study results are presented in Table II. The full Finder system achieved a SR of 63.4% and an average MSPL of 0.389. In contrast, removing the scene-level object correlations (Finder w/o StO) caused a decrease in performance, with an SR of 61.5%, and an MSPL of 0.364. Without the scene-level correlations, the robot disregarded areas that were semantically correlated to the target objects. For example, the robot might skip exploring a kitchen-like area when searching for a toaster. Similarly, removing object-to-object correlations (Finder w/o OtO) further reduced the SR to 58.3% and the MSPL to 0.337. Without these correlations, the robot could not exploit the cooccurrence of objects that typically appear together. For instance, when searching for a TV, the robot might miss areas with a remote control or TV stand, which are often found near TVs. Thus, the absence of these score maps resulted in a degraded understanding of the semantic relationships between scene objects, target objects and the environment, leading to reduced search performance.

C. Simulation Scalability Study

1) *Procedure*: We evaluated the performance of Finder in terms of exploration time for increasing number of target objects. The objective is to investigate Finder’s efficiency as task complexity grows. We conducted 100 successful episodes for each experimental condition, varying the number of target objects from 1 to 8, using the HM3D dataset.

2) *Results*: The results of scalability study are presented in Fig. 4. Overall, the average exploration time increased as the number of target objects increased. Exploration time increased from 67 steps to over 200 steps as the number of target objects exceeded one, indicating that the search task becomes significantly more complex when transitioning from SOS to MOS. However, the exploration time gradually converged to around 300 steps, with only marginal increases as the number of objects increased. This convergence suggests that Finder effectively explores a substantial portion of the environment within this time, enabling it to find all target objects efficiently. These results demonstrate Finder’s capability to scale in MOS tasks.

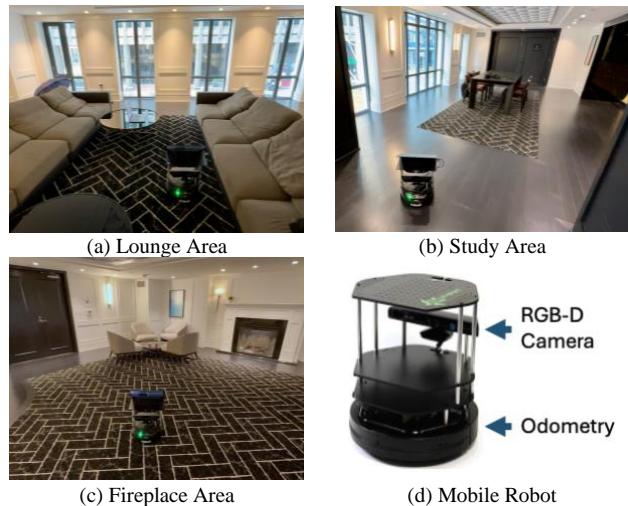


Fig. 5. Multi-room indoor environment with varying areas (a)-(c). Mobile robot equipped with RGB-D camera and odometry sensor.

D. Sim-to-Real Study

We conducted real-world experiments in an object-dense multi-area indoor building environment with a total area of 121.5 m², Fig. 5(a)-(c). Namely, it consists of lounge area, study area, and a fireplace area. A TurtleBot was deployed with a Kinect camera for obtaining RGB-D image observations, Fig. 5(d). We used a set of target objects including garbage bin, fireplace, laptop, shoes, backpack, lamp, and umbrella. We sampled 3, 4, 5 objects from the set of target object lists for each trial to evaluate: 1) the generalizability of Finder in real-world environments, and 2) its ability to find increasing number of objects. For the navigation controller, we used A* as the global planner and Time Elastic Band Planner [51] as the local planner to generate robot velocities to navigate to the selected waypoint. The videos of Finder addressing the MOS task in both simulated and real-world environments are provided on <https://find-all-my-things.github.io/>.

VI. CONCLUSION

In this paper, we introduced Finder, a novel VLM-based approach to address the MOS problem across various environments. The proposed method integrates multi-channel Scene-to-Object and Object-to-Object score maps generated from VLMs for effective waypoint selecting during object search. These score maps enable simultaneous tracking and reasoning about multiple objects, while leveraging both scene-level and object-level semantic correlations. Extensive experiments were conducted in simulated and real-world environments against SOTA methods. The results demonstrated that Finder outperformed existing multi-object search methods. Ablation studies further confirmed the effectiveness of our multi-channel score maps and fusion technique, while scalability study demonstrated Finder’s performance with increasing number of target objects. Future work includes extending Finder to handle dynamic objects and interactive search scenarios where objects may be hidden, moved or stored.

VII. REFERENCES

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