OpenFMNav: Towards Open-Set Zero-Shot Object Navigation via Vision-Language Foundation Models

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Abstract

Object navigation (ObjectNav) requires an agent to navigate through unseen environments to find queried objects. Many previous methods attempted to solve this task by relying on supervised or reinforcement learning, where they are trained on limited household datasets with close-set objects. However, two key challenges are unsolved: understanding free-form natural language instructions that demand open-set objects, and generalizing to new environments in a zero-shot manner. Aiming to solve the two challenges, in this paper, we propose **OpenFMNav**, an **Open**-set **F**oundation **M**odel based framework for zero-shot object **Nav**igation. We first unleash the reasoning abilities of large language models (LLMs) to extract proposed objects from natural language instructions that meet the user's demand. We then leverage the generalizability of large vision language models (VLMs) to actively discover and detect candidate objects from the scene, building a *Versatile Semantic Score Map (VSSM)*. Then, by conducting common sense reasoning on *VSSM*, our method can perform effective language-guided exploration and exploitation of the scene and finally reach the goal. By leveraging the reasoning and generalizing abilities of foundation models, our method can understand free-form human instructions and perform effective open-set zero-shot navigation in diverse environments. Extensive experiments on the HM3D ObjectNav benchmark show that our method surpasses all the strong baselines on all metrics, proving our method's effectiveness. Furthermore, we perform real robot demonstrations to validate our method's open-set-ness and generalizability to real-world environments.

1 Introduction

As a fundamental task in robotics and embodied AI, object navigation requires an agent to navigate through unseen environments to find queried objects. Compared to other robotic tasks, it is particularly important because it is a prerequisite for robots to interact with objects. To address this issue, several household datasets and benchmarks, such as MP3D (Chang et al., 2017), Gibson (Xia et al., 2018) and HM3D (Ramakrishnan et al., 2021) are proposed. Many previous studies (Chaplot et al., 2020a; Ramrakhya et al., 2022; Zhang et al., 2023) have attempted to solve this problem through supervised or reinforcement learning, where they are trained on particular household datasets above with close-set objects and comparable environments.

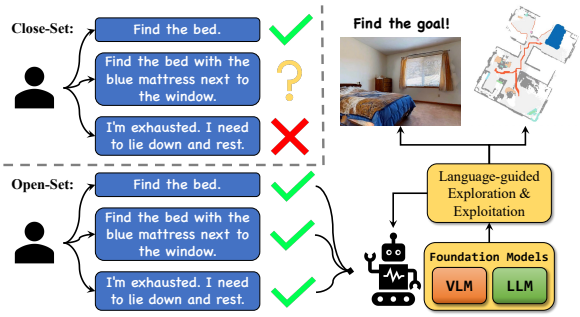


Figure 1: Leveraging foundation models, our proposed OpenFMNav can follow free-form natural language instructions with open-set objects and achieve effective zero-shot object navigation.

However, there are two significant challenges remaining unsolved. **First**, as shown in Fig 1, in many scenarios, instead of only mentioning an object category (e.g., *"Find the bed."*), humans often provide free-form instructions, either specifying objects with specific characteristics (e.g., *"Find the bed with the blue mattress next to the window."*), or expressing their demand without explicitly mentioning the object (e.g., *"I'm exhausted. I need to lie down and rest."*). These natural language instructions may demand open-set objects not included in the training vocabulary. In such cases, existing supervised or reinforcement learning-based methods fail to understand these natural language

instructions since they require specific object categories and were trained to perform close-set object detection. **Second**, due to the data scarcity of embodied navigation (Gu et al., 2022), these methods are typically trained on limited datasets that only cover household environments, which causes severe overfitting issues and prevents them from generalizing to unseen and diverse environments, let alone performing zero-shot navigation.

To address the first challenge, some initial progress has been made in understanding free-form natural language instructions with open-set objects. For instance, demand-driven navigation (DDN) was proposed by Wang et al. (2023) to map human instructions to a demand-conditioned attribute space. However, it is still limited to household settings and cannot be generalized to various environments. Another approach was suggested by Majumdar et al. (2023), which involves finding objects with specific attributes and eliminating distractors. However, it needs 2D occupancy maps and pre-exploration of the scene in the beginning, which are unavailable in unseen environments.

On the second challenge, recent years have witnessed progress in Zero-Shot Object Navigation (ZSON) (Majumdar et al., 2022; Gadre et al., 2023; Yokoyama et al., 2023; Zhou et al., 2023; Dorbala et al., 2023; Yu et al., 2023; Shah et al., 2023; Cai et al., 2023). However, some of these works (Majumdar et al., 2022; Yu et al., 2023; Cai et al., 2023) require data to train specific modules such as locomotion planning, and hence are not real "Zero-Shot". More importantly, these methods cannot conduct explicit and comprehensive reasoning on free-form natural language instructions, leading to their low performance and preventing them from being applied to many downstream robotic tasks.

To better address the aforementioned two key challenges, in this paper, we propose OpenFMNav, a novel framework based on foundation models to achieve effective open-set zero-shot navigation. To this end, we utilize foundation models to leverage their reasoning abilities and generalizability to interpret human instructions and actively explore the environment. To be more specific, we first leverage large language models to extract initially proposed objects from natural language instructions and merge them with user-defined prior objects and objects discovered by vision language models. We then construct an object prompt to detect and segment objects from the observation image, leveraging large vision language models. By using depth images to project the segmentation masks to the space, we can build a 2D top-down *Versatile Semantic Score Map (VSSM)* of the whole scene, on which we sample frontiers with semantic information for a large language model to conduct common sense reasoning and wisely choose frontiers to guide navigation. This way, we can perform language-guided exploration and exploitation of the scene and achieve effective open-set zero-shot object navigation without prior training on any household datasets. Moreover, unlike previous map-based methods such as Zhou et al. (2023); Yu et al. (2023); Shah et al. (2023); Yokoyama et al. (2023), the *VSSM* produced by our method will keep updating during the navigation, which better adapts to changing environments and can be further used in downstream robotic tasks, such as multi-goal navigation and mobile manipulation.

We conduct extensive experiments on the HM3D ObjectNav benchmark (Yadav et al., 2022a). Results show that our method outperforms the State-of-the-Art open-set zero-shot object navigation method (Zhou et al., 2023) by over 15% on success rate and surpasses all the strong baselines on all metrics, validating the effectiveness and superiority of our framework. Additionally, our method has been proven to understand free-form natural language instructions with open-set objects and generalize well to real-world environments through real robot demonstrations.

2 Related Work

2.1 Embodied Navigation

Embodied navigation is a fundamental yet challenging task in robotics and embodied AI since it is the precursor to many downstream robotic tasks, such as object manipulation and teleoperation. In such scenarios, given a specific goal and egocentric observations, agents are required to move to a desired location within a maximum timestep.

Due to the importance of embodied navigation, recent years have witnessed several branches of navigation tasks with different goal specifications. For instance, point goal navigation (PointNav) (Wijmans et al., 2019; Savva et al., 2019) uses point coordinates in the space as the goal; image goal navigation (ImageNav) (Chaplot et al., 2020b; Savinov et al., 2018) requires the agent to move where the given image is taken; and vision-language navigation (VLN) (Anderson et al., 2018; Ku et al., 2020) requires the agent to follow step-by-step in-

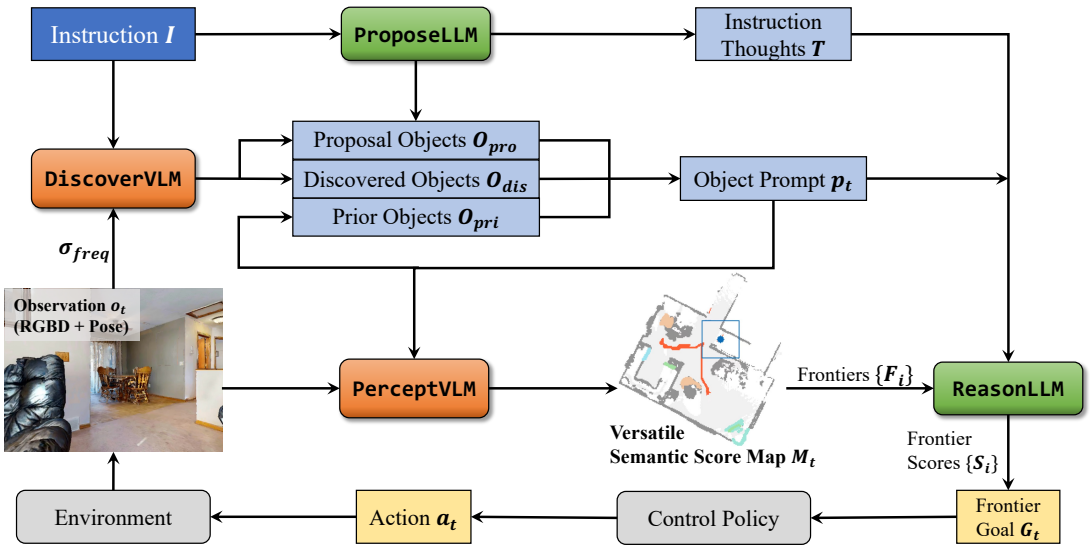


Figure 2: The framework of our proposed OpenFMNav. Based on the natural language instruction and observations, we utilize foundation models to interpret human instructions and construct a *Versatile Semantic Score Map (VSSM)*, on which we perform common sense reasoning and scoring to conduct language-guided frontier-based exploration.

structions to reach the location; and in object navigation (ObjectNav) (Batra et al., 2020), the agent is required to find objects of specified categories.

Compared to vision-language navigation (VLN), which offers detailed and step-by-step instructions, object navigation is particularly challenging since the agent needs to do semantic recognition to find the goal and needs more efficient exploration than VLN since there are no step-by-step instructions (Chen et al., 2023). It is also more common in real life that humans will give ambiguous demands (Wang et al., 2023) rather than detailed instructions in VLN. Additionally, VLN datasets (Anderson et al., 2018; Ku et al., 2020) are typically discretized into checker-like waypoint graphs, which makes it difficult to deploy algorithms in the real world, while on the other hand, ObjectNav is **continuous** and more **object-centric** so that it can be easily deployed and extended to many downstream robotic tasks like object manipulation.

To take a step further, in this paper, we propose a solution to the problem of open-set-ness in ObjectNav by introducing a framework that transforms the paradigm of ObjectNav from given close-set category names to free-form natural language instructions with open-set objects. This transformation will help bridge the interaction between humans and embodied agents, making it more useful in real-world applications. Compared to existing works (Majumdar et al., 2023; Wang et al., 2023), our method doesn't need prior occupancy maps and pre-exploration in the beginning and thus can navigate in unseen environments. Furthermore, our method addresses the overfitting issue in embodied navigation and easily generalizes to the real world in a zero-shot manner, enabling intelligent robot agents to navigate in more diverse environments.

2.2 Zero-Shot Object Navigation

As Gu et al. (2022) elaborates, embodied navigation faces a severe challenge of data scarcity, limiting the amount and distribution of available data for training. Methods directly supervised on these limited data cannot generalize to diverse real-world environments.

Therefore, recent years have witnessed great progress in Zero-Shot Object Navigation (ZSON). Methods proposed by Majumdar et al. (2022); Gadre et al. (2023); Yokoyama et al. (2023) leverage CLIP (Radford et al., 2021) or BLIP-2 (Li et al., 2023) embedded features to compute similarities between object goal and input image and construct an implicit map for certain goal objects to guide navigation. Other methods, such as those proposed by Zhou et al. (2023); Dorbala et al. (2023); Yu et al. (2023); Shah et al. (2023), leverage object detectors to construct metric maps and use large language models to conduct reasoning. Cai et al. (2023) leverages foundation models to perform basic image processing and trains a locomotion module to navigate to certain chosen pixel points.

2.3 Foundation Models

Foundation models (Bommasani et al., 2022) are large-scale models that are pre-trained on vast amounts of data and can perform general tasks. The sheer volume of pretraining data endows them with exceptional generalizability, which allows them to perform zero-shot inference. Moreover, the extensive training data helps foundation models acquire common sense about our physical world, making them ideal for real-world applications.

Foundation models, particularly the large language models (LLMs), also have an intriguing feature — In-Context Learning (ICL) (Dong et al., 2023). This feature enables these models to follow pre-defined instructions to ground their output into certain patterns. By combining ICL with common sense learned from the large-scale data, foundation models can effectively perform semantic reasoning and guesswork to provide intuitions of possible exploration directions like human beings, as illustrated in Zhou et al. (2023); Yu et al. (2023); Shah et al. (2023). For example, if the goal is a "toilet", from common sense it is highly possible to find it around an area that contains a "bathtub".

According to different modalities, foundation models can be mainly divided into Visual Foundation Models (VFM), such as SAM (Kirillov et al., 2023), Large Language Models (LLM), such as GPT-3.5/GPT-4 (Ouyang et al., 2022; OpenAI, 2023) and LLaMA/LLaMA-2 (Touvron et al., 2023a,b), and Vision Language Models (VLM), such as GPT-4V (Yang et al., 2023b), CLIP (Radford et al., 2021), Grounded-SAM (Liu et al., 2023), etc. There are also foundation models covering other modalities, such as audio (Yang et al., 2023a) and video (Xu et al., 2021). In this paper, we use VLMs and LLMs since our setting only involves vision and language modalities.

3 Method

3.1 Problem Statement and Method Overview

Problem Statement. As shown in Fig. 1, in an unfamiliar environment, given a natural language instruction I, an embodied agent needs to explore the environment in search of a certain queried object. At timestep t, the agent is provided with egocentric RGBD observation o_t and should output an action a_t such as `move_forward`, `turn_left`, `stop`, etc. A successful navigation is defined as finding the queried object within the maximum navigation timestep.

Method Overview. As shown in Fig. 2, given a starting point and human instruction I, the agent first utilizes the ProposeLLM to propose possible objects to meet the instruction. At timestep t, the agent can leverage the DiscoverVLM to discover new objects from the scene and check whether they can meet the instruction. Along with prior defined objects and proposal objects, the full object list is then converted into an object prompt p_t for foundation models to reason. Given current RGBD observation o_t, the PerceptVLM will detect and segment object masks based on p_t, constructing a *Versatile Semantic Score Map (VSSM)* M_t, on which possible exploration frontiers are sampled. Finally, the ReasonLLM will conduct common sense reasoning based on the semantic information of frontiers and give the next frontier goal G_t to explore, which will be executed by an underlying control policy to output low-level actions. The whole process is looped until the object is found or the agent fails.

3.2 Discovery and Perception

Discovery. Given a free-form human instruction I that may contain open-set objects, we first leverage a ProposeLLM to get all possible proposal objects O_{pro} that can satisfy the instruction. Each proposal object contains attributes such as color, location, etc, to satisfy fine-grained instructions. At timestep t, given egocentric RGBD and pose observations o_t, we propose a DiscoverVLM using GPT-4V (Yang et al., 2023b) that actively discovers novel objects O_{dis} from the RGB image. Meanwhile, the DiscoverVLM also conducts reasoning on the instruction, trying to discover objects that potentially meet the instruction and update O_{pro}. Extracting novel objects from the environment is essential for open-set navigation since they may contain scene-specific information that helps to find the goal. To save time and cost, the DiscoverVLM is randomly activated by a frequency parameter σ_{freq}.

Perception. After getting proposal objects O_{pro} and discovered objects O_{dis}, we merge them with prior objects O_{pri} to construct an object prompt p_t to feed into our PerceptVLM based on Grounded-SAM (Liu et al., 2023) to detect and segment all the appearing objects in p_t from the RGB image of o_t. Note that due to the BERT encoder (Devlin et al., 2019) and powerful SAM backbone (Kirillov et al., 2023) in the PerceptVLM, it can achieve open-set object detection in high granularities. This process will output object masks with confidence scores for further mapping and reasoning.

3.3 Mapping and Reasoning

Mapping. At timestep t, based on the confidence scores of object masks produced by PerceptVLM and the depth image and pose in o_t, we project the masks to the top-down 2D space and construct a *Versatile Semantic Score Map (VSSM)* $M_t \in \mathbb{R}^{H \times W \times (C+2)}$, which contains C channels of object semantics, and two channels of the occupied area and explored area, with a resolution of $H \times W$. Each element in the map is a score in $[0, 1]$ instead of binary labels. Since we continuously discover novel objects from the environment, the C is versatile so that we can keep updating the map, enabling life-long learning and downstream robotic tasks. Also, instead of filling binary labels into semantic channels, we fill each semantic channel with confidence scores, with which we can easily update the map if there is a change in the environment.

Reasoning. Based on M_t, we can sample frontiers $\{F_i\}$ with semantic information in unexplored areas for further exploration. To choose the next frontier to explore, we leverage ReasonLLM by unleashing the power of LLM's common sense reasoning. Specifically, given the semantic information around each frontier, we construct a query template in the form of "`This area contains A, B and C.`". Combined with the thought T produced by Chain-of-Thought (Wei et al., 2022) prompting from ProposeLLM and the object prompt p_t, the ReasonLLM will conduct common sense reasoning and rate these frontiers to pick one frontier goal G_t which is most likely to find the goal. This frontier goal G_t will guide the agent for further exploration and produce low-level actions to control the agent.

Instead of just asking the LLM which frontier to go to, we introduce another reasoning process, which prompts LLMs to rate these frontiers $\{F_i\}$ to scores $\{S_i\}$, in which $S_i \in [0, 1]$, indicating the likelihood to find the goal. Then, the frontier with the highest score will be picked out for further exploration. By introducing this rating process, ReasonLLM can map its common sense to concrete numbers that reflect the actual ranking, leading to better reasoning. We verified its effectiveness in Section 4.5. It's also worth mentioning that to balance exploration and exploitation, ReasonLLM is activated at regular timestep intervals δ to update G_t. At other timesteps, the frontier goal G_t remains unchanged to fully explore the previously chosen frontier $G_{t-\delta}$.

Algorithm 1: Pseudo-Code of the Overall Algorithm for OpenFMNav

```
Data: Natural Language Instruction I, Prior Objects
      O_pri, Discovery Frequency σ_freq, Frontier
      Goal Update Interval δ
t ← 0;
done ← False;
G_0, M_0, O_dis ← None;
O_pro, T ← ProposeLLM(I);
while not done do
    o_t ← getObservation();
    if toDiscover(σ_freq) then
        O_dis, O_pro ← DiscoverVLM(o_t, I);
    end
    p_t ← getPrompt(O_pro, O_dis, O_pri);
    Masks ← PerceptVLM(o_t, p_t);
    M_t ← semanticMapping(M_{t-1}, Masks, o_t);
    if O_pro in M_t then
        G_t ← getLocation(M_t, O_pro);
    else
        if t % δ == 0 then
            {F_i} ← sampleFrontiers(M_t);
            {S_i} ← ReasonLLM({F_i}, p_t, T);
            G_t ← getLocation(M_t, argmax({S_i}));
        else
            G_t ← G_{t-1};
        end
    end
    O_pri ← updateObj(O_pro, O_dis, O_pri);
    a_t ← FMMPlanner(M_t, G_t);
    done ← stepAction(a_t, t);
    t ← t + 1;
end
```

After obtaining the frontier goal and the occupancy channel in M_t, we utilize a control policy based on the Fast Marching Method (FMM) (Sethian, 1999) to output a low-level action a_t to control the agent. This closes the loop and goes to the next timestep $t + 1$.

We present the whole process of our OpenFMNav algorithm in Algorithm 1.

4 Experiments

In this section, we evaluate our method comprehensively in simulation to show our method's effectiveness compared to baseline methods. We also conducted ablation studies to validate the effectiveness of our framework design.

4.1 Experimental Setup

In the simulation, we evaluate on the HM3D ObjectNav benchmark based on the Habitat Matterport 3D Semantics Dataset (Yadav et al., 2022b), which contains 80 train scenes and 20 validation scenes. We utilize the validation scenes for evaluation. There are, in total, 2000 episodes and six goal

Method	Open-Set	Zero-Shot	SR (%) ↑	SPL ↑
FBE (Gervet et al., 2023)	×	✓	23.7	0.123
SemExp (Chaplot et al., 2020a)	×	×	37.9	0.188
ZSON (Majumdar et al., 2022)	✓	×	25.5	0.126
GoW (Gadre et al., 2023)	✓	✓	32.0	0.181
ESC (Zhou et al., 2023)	✓	✓	38.5	0.220
L3MVN (Yu et al., 2023)	×	✓	50.4	0.231
PixNav (Cai et al., 2023)	✓	×	37.9	0.205
OpenFMNav (Ours)	✓	✓	**54.9**	**0.244**

Table 1: Comparison between different methods on the HM3D ObjectNav benchmark. Our method outperforms all the baseline methods on all metrics and achieves open-set zero-shot object navigation.

classes (chair, couch, potted plant, bed, toilet, and tv) in the dataset. The action space of the robot agent is {`stop`, `move_forward`, `turn_left`, `turn_right`, `look_up`, `look_down`}. The forward distance is set to 0.25m, and the rotation angle is set to 30 degrees.

Following previous works (Zhou et al., 2023; Cai et al., 2023), we utilize **Success Rate (SR)** metric to measure whether an agent can find our desired objects. We also report results of **Success weighted by Path Length (SPL)** to measure the navigation efficiency.

4.2 Implementation Details

In our method, the foundation models we use are: GPT-4 (text-only) (OpenAI, 2023) for ProposeLLM and ReasonLLM, and GPT-4V (Yang et al., 2023b) for DiscoverVLM. For PerceptVLM, we utilize Grounded-SAM, which first leverages Grounding DINO (Liu et al., 2023) to produce bounding boxes given the RGB image in o_t and object prompt p_t, and then leverages Segment Anything Model (SAM) (Kirillov et al., 2023) for each bounding box to produce high-granularity object masks for semantic mapping.

Moreover, we utilize the Chain-of-Thought (CoT) (Wei et al., 2022) prompting technique to fully exploit the reasoning abilities of ProposeLLM, ReasonLLM and DiscoverVLM. The prompts we used can be found in Appendix C.

In the simulation, we set the update interval δ to 20 timesteps, discovery frequency σ_{freq} to 0.01, and the initial prior objects to a subset of HM3D object categories, which can be found in Appendix B.

4.3 Baseline Methods

We compare our method with several recent works, with a focus on open-set and zero-shot object navigation baselines to verify our framework's effectiveness. We classify these baseline methods into "Open-Set" and "Zero-Shot" or not. Here, we define "Open-Set" as that the method can find whatever object category we want, and define "Zero-Shot" as that the agent hasn't been trained or finetuned on ***any*** of the data previously, including images, episodes, and locomotion planning. The baseline methods are as follows:

- **FBE** (Gervet et al., 2023). This baseline method employs a classical robotics pipeline for mapping and a frontier-based exploration algorithm.
- **SemExp** (Chaplot et al., 2020a). A method that explores and searches for the target using close-set semantic maps and reinforcement learning.
- **ZSON** (Majumdar et al., 2022). An RGB-based zero-shot object navigation baseline using CLIP (Radford et al., 2021) to embed scene features. It is trained on ImageNav and directly transferred to ObjectNav.
- **GoW** (Gadre et al., 2023). A modification of CoW (Gadre et al., 2023) implemented by Zhou et al. (2023) that uses GLIP (Li* et al., 2022) for object detection and the vanilla fronter-based exploration method.
- **ESC** (Zhou et al., 2023). A map-based zero-shot object navigation baseline that uses GLIP (Li* et al., 2022) to detect objects and rooms, and combines LLM with soft commonsense constraints for planning.
- **L3MVN** (Yu et al., 2023). An LLM-based baseline that uses a close-set object detector (Jiang et al., 2018) and LLMs to conduct frontier-based exploration.

Method	SR (%) ↑	SPL ↑
w/o GPT-4	53.6	0.230
w/o CoT	51.8	0.208
w/o Discovery	50.0	0.222
w/o Scoring	50.0	0.208
Ours	**55.4**	**0.239**

Table 2: Ablation studies on different components of our method. Experiments are conducted under the same uniformly sampled episodes.

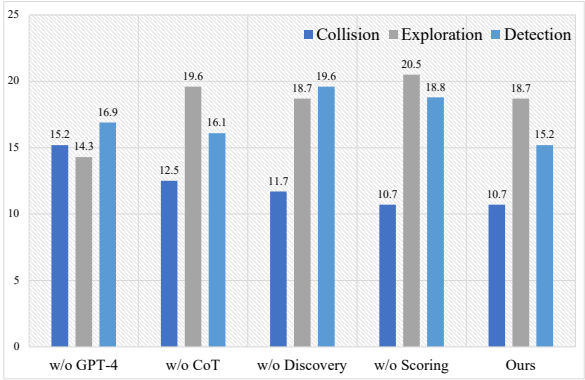


Figure 3: Types and percentages of failure cases in ablation methods.

- **PixNav** (Cai et al., 2023). A recent work solely using foundation models to pick out navigation pixels and train a locomotion module to navigate to chosen pixels.

4.4 Results and Analysis

We report the main results in Table 1. Our method surpasses all the baselines on both Success Rate (SR) and Success weighted by Path Length (SPL), especially compared with open-set zero-shot methods. Our method surpasses the previous State-of-the-Art method on open-set zero-shot object navigation (Zhou et al., 2023) by over 15% on the success rate metric, suggesting that our framework is indeed effective.

First, we compare our method with previous semantic map based methods, such as SemExp (Chaplot et al., 2020a), ESC (Zhou et al., 2023) and L3MVN (Yu et al., 2023). The results show that our method performs better since we utilize DiscoverVLM to construct *VSSM* with versatile out-of-vocabulary class labels, such as "marble statue" and "range hood", which helps to alleviate the issue of limited categories and enriches the semantic information of the environment. Also, compared to these methods, our method achieves open-set navigation, which better adapts to complex situations and real-world applications.

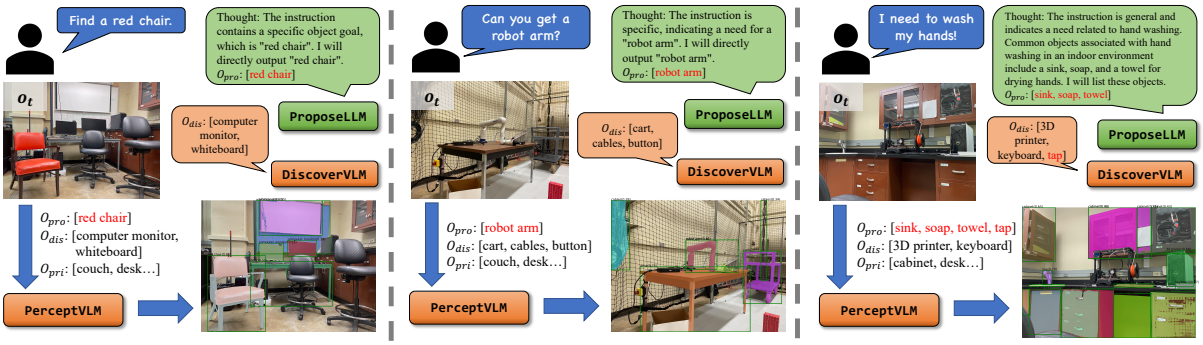
Compared with other open-set baselines, such as PixNav (Cai et al., 2023), ZSON (Majumdar et al., 2022) and GoW (Gadre et al., 2023), our method constructs an explicit map where all discovered objects are presented. Therefore, we can boost LLMs' reasoning abilities to balance between exploration and exploitation and make the agent move to where the goal is most likely to be. Also, the map constructed by our method is maintained and updated, which is perfect for life-long learning, enabling downstream robotic tasks with further natural language instructions, while methods like Gadre et al. (2023); Yokoyama et al. (2023) only construct implicit maps for a certain goal, which is useless after the navigation.

4.5 Ablation Studies

Probing deeper into our method design, we also performed ablation studies on various components of our pipeline. Note that to save time and cost, we test all the ablation methods on a subset of the full dataset under the same uniformly sampled episodes so that there can be slight differences in the result of our method. Table 2 shows that modifying multiple components of our framework leads to significantly worse performance. We also categorized the failure cases into different types and report their percentages in Fig. 3, in which **Collision** refers to the situation where the agent cannot avoid colliding with the environment, **Exploration** means the agent times out while trying to find the goal, and **Detection** means the agent mistakenly identifies a wrong object as the goal.

Effectiveness of using larger models. First, we analyze the usage of GPT-4 for LLMs. Compared to only using GPT-3.5, using larger GPT-4 achieves better performance (+1.8%), reducing failure cases of Collision and Detection. However, the percentage of Exploration is slightly higher, showing that larger models have more diverse answers that encourage more exploration, which potentially causes more time out.

Effectiveness of our joint reasoning pipeline. Then, we analyze different foundation model components. We found that using CoT prompting (+3.6%) and scoring prompting (+5.4%) are essential to the strong performance of OpenFMNav since they generate more reasoning chains that elicit the common sense of large language mod-



(a) Robust to distractors (b) Robust to open-set objects (c) Robust to free-form demands

Figure 4: Qualitative studies in the real world. Text marked in red indicates objects that potentially satisfy the instruction. Results show that our method is robust to natural language instructions, including distractors, open-set objects and free-form demands.

els. Also, compared to restricting the object set, leveraging DiscoverVLM not only enables more free-form natural language instructions from users' input but also enriches the scene's semantics, which helps the reasoning for frontier-based exploration and improves performance (+5.4%). These efforts reduce failure cases of all categories.

5 Navigation in the Real World

We further conduct real robot demonstrations to show our method's ability to understand free-form natural language instructions and perform open-set zero-shot navigation in the real world.

5.1 Real Robot Setup

For robots, we use a TurtleBot3 Burger robot with scalable structures to navigate on the ground. We limit its action space to {`stop`, `move_forward`, `turn_left`, `turn_right`}. As in the simulation, we set the forward distance to 0.25m and the rotation angle to 30 degrees. For robotic perception, we use an Intel RealSense SR300 depth camera to capture RGBD images.

For real-world environments, we select an office with sufficient space and various objects for the robot to navigate. The office contains not only common objects like "chair", "desk", "computer" and "cabinet", but also less common ones like "robot arm" and "3D printer".

5.2 Qualitative Studies

We conduct qualitative studies on our OpenFMNav in the real world, as shown in Fig. 4. The results show that our method can perform effective zero-shot navigation in the real world given free-form natural language instructions. Especially, our method is robust to distractors, open-set objects and free-form demands.

For distractors, rather than object categories, our proposed ProposeLLM can extract the attributes in the instruction ("red chair"), which can be further detected and segmented by PerceptVLM. In Fig. 4(a), we can see that, among the three chairs in the observation, only the red chair is masked.

For open-set objects, due to the large-scale training data of foundation models, our method can also navigate to objects that are uncommon and out-of-vocabulary, such as the "robot arm" in Fig. 4(b).

Another intriguing feature of our method is that our method can adaptively add up goals in the navigation. This happens when the instruction is a free-form demand for ambiguous objects. For example, in Fig. 4(c), when the user needs to wash hands, the ProposeLLM first proposed "sink", "soap" and "towel", but they are not necessarily present in the scene. When the agent explores the environment, the DiscoverVLM can actively discover what's new in the environment and reason about whether they can potentially fulfill the user's demand. In this case, a "tap" is discovered and identified as a goal so that the agent can directly navigate to it without further exploration. This is extremely helpful when the humans are also unaware of the scene details.

6 Conclusions

In this paper, we presented a novel framework, OpenFMNav, for open-set zero-shot object navigation. By leveraging foundation models, our method could understand free-form natural language instructions, conduct reasoning, and perform effective zero-shot object navigation. Extensive experiments showed the superiority of our framework. Finally, we conducted real robot demonstrations to validate our method's open-set-ness and generalizability to real-world environments.

Ethics Statement

In this paper, we present a method for open-set zero-shot object navigation. This method can be used for zero-shot robotic navigation in diverse scenarios, such as home robots, warehouse robots, and so on. Our work further addresses the issue of ambiguous or free-form natural language instructions, benefitting the interaction between humans and robots. However, foundation models can have safety issues and risks such as privacy leaks and jailbreaking (Deng et al., 2023; Chao et al., 2023), which need to be further addressed.

Limitations

While extensive experiments validate the effectiveness of our method design, there exist a number of limitations in our work. First, our method requires relatively accurate depth sensors to build the 2D map, while the observed depths may have much noise in reality, causing performance degradation. Moreover, we acknowledge that our method requires stable Internet connections to get responses from APIs of foundation models, limiting the potential of large-scale deployment in harsh environments. We hope future works on depth sensing, LLM quantization, and edge computing can mitigate such limitations.

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A API Usage

Model Name	API Name
ProposeLLM	`gpt-4-1106-preview`
DiscoverVLM	`gpt-4-vision-preview`
ReasonLLM	`gpt-4-1106-preview`

Table 3: API usage

B Hyperparameters

Parameter	Value
Discovery Frequency σ_{freq}	0.01
Frontier Goal Update Interval δ	20
Confidence Score Threshold	0.55
LLM/VLM Temperature	0
Initial Prior Objects O_{pri}	See Fig. 5

Table 4: Hyperparameters

chair, bed, plant, toilet, tv, couch, desk, refrigerator, sink, bathtub, shower, towel, painting, trashcan, stairs

Figure 5: Initial prior objects O_{pri}

C Prompts

C.1 Prompts for ProposeLLM

The prompts for ReasonLLM are shown in Fig. 6.

```
SYSTEM_PROMPT="""You are an intelligent embodied agent called ProposeLLM that follows an instruction to navigate in a real indoor environment. Your goal is to propose a list of objects that can satisfy the user's need.

You are firstly given an instruction that indicates the user's need.

If the instruction contains a specific goal object, like "go to the bed" or "find the red bottle", you should directly output the goal object with its possible attributes, like "bed" or "red bottle".

Otherwise, if the instruction is more general, like "I'm so thirsty", you should inference via common sense which objects are feasible and output a list of objects that can satisfy the user's need, like "bottle", "cup", "refrigerator", etc.

Notice that your output should be a list of objects with their possible attributes, even if there is only one object in the list."""

USER1="""go to the bed"""

ASSISTANT1="""Thought: The instruction contains a specific object goal, so I will directly output "bed".

Answer: ["bed"]"""

USER2="""I have been standing for hours. I need some place to sit down and rest."""

ASSISTANT2="""Thought: The instruction is quite general, so I will use my common sense. The user needs some place to sit down, so candidate objects in an indoor scene can be chair, couch, etc. I will output a list of these objects.

Answer: ["chair", "couch"]"""
```

Figure 6: Prompts for ProposeLLM

C.2 Prompts for DiscoverVLM

The prompts for ReasonLLM are shown in Fig. 7.

```
SYSTEM_PROMPT="""You are an intelligent assistant called DiscoverVLM that can understand natural language and scene images. Given a list of objects and an image, your goal is to discover new objects in the image that are not in the list.

You should consider the following rules when discovering new objects:

(1) You should first consider, what's in the image? Note that you should only include objects in the house, and avoid things that are part of the house, like ceiling, wall, floor, window etc and avoid room names, like bedroom, kitchen, etc.

(2) Considering the given object list, you should only output things that are not in the list or are not similar to things in the list because your duty is to discover new things. For example, if the given object list contains "couch" or "tv", you should not output "sofa" or "television" because they are similar.

(3) Confirm that the objects you output are in the image. For example, if the image is a bedroom, you should not output "bathtub" because it is impossible to find a bathtub in a bedroom. And also confirm the objects you output don't violate rule (1).

(4) Avoid objects are common everywhere. For example, objects like light switch and door are present in every room, so you should not output them.

Your output should be in the form of "Answer: <list of objects>" such as:

Answer: ["chair", "bed", "bottle"]
"""

USER="""What objects can you see in the image?"""
```

Figure 7: Prompts for DiscoverVLM

C.3 Prompts for PerceptVLM

For PerceptVLM, given the current object list, we use dots to separate each object as the object prompt p_t.

For example, if the object list is `[chair, bed, plant, toilet, tv, couch]`, the object prompt is "`chair.bed.plant.toilet.tv.couch`".

C.4 Prompts for ReasonLLM

The prompts for ReasonLLM are shown in Fig. 8.

```
SYSTEM_PROMPT="""You are an intelligent embodied agent called ReasonLLM that follows an instruction to navigate in an indoor environment. You are firstly given
an object goal class for you to find, which is called the goal.

Then, at each step, your task is to take several descriptions of what an area contains to output scores for these areas to contain the goal. Each score is a
floating point number between 0 and 1.

Your output should be a list of scores.

At each step, you should consider:

(1) For each description, according to what the area contains, is it possible that the goal is also in this area? To better do reasoning, you can imagine what
kind of room the area is in, for example, a bedroom, a living room, a bathroom, etc. Based on the common sense, you can judge the possibility that the goal to
be in this area.

(2) If the goal class is already in the description, the score should be 1 without any hesitation.

(3) If one area contains nothing, it is still possible that the goal is in that area. Give a score of 0.4 to 0.6. Score the area higher in that case when other
areas are not likely to contain the goal.

(4) If there are no current frontiers, skip the thought and output 'No frontiers'."""

USER1="""Goal: toilet

- Description 0: The area contains a towel, a bathtub and a sink.

- Description 1: The area contains a bed and a plant.

- Description 2: The area contains a sofa, a TV and a table.

"""

ASSISTANT1="""Thought: Let's analyze each description.

- Description 0: this area contains a bathtub and a sink, so it is possibly a bathroom, and the goal is toilet, so it is possible that the goal is in this area,
I will give a score of 0.9

- Description 1: this area contains a bed and a plant, so it is possibly a bedroom, and the goal is toilet, so it is not likely that the goal is in this area. I
will give it a 0.2

- Description 2: this area contains a sofa, a TV and a table, so it is possibly a living room, and the goal is toilet, so it is also not likely that the goal is
in this area. I will give it a 0.3

Answer: [0.9, 0.2, 0.3]"""

USER2="""Goal: bed

- Description 0: The area contains a towel, a bathtub and a sink.

- Description 1: The area contains a bed and a plant.

- Description 2: The area contains a sofa, a TV and a table.

"""

ASSISTANT2="""Thought: Let's analyze each description.

- Description 0: this area contains a bathtub and a sink, so it is possibly a bathroom, and the goal is bed, so it is not possible that the goal is in this
area. My score is 0.1

- Description 1: this area contains a bed, which is the goal, so the score is 1

- Description 2: this area contains a sofa, a TV and a table, so it is possibly a living room. The goal is a bed, so it can be near this area. I will give it a
0.5

Answer: [0.1, 1, 0.5]"""
```

Figure 8: Prompts for ReasonLLM