Grounding Spatiotemporal Navigation Commands Using Large Language and Vision Models

Jason Xinyu Liu, Ankit Shah, George Konidaris, Stefanie Tellex, and David Paulius

***Abstract*— Grounding spatiotemporal navigation commands to structured task specifications enables autonomous robots to understand a broad range of natural language commands and solve long-horizon tasks with safety guarantees. Prior works mostly focus on grounding spatial or temporally extended language for robots. We propose a modular system that leverages pretrained large language and vision models and multimodal semantic information to ground spatiotemporal navigation commands in novel city-scale environments without retraining. Our language grounding system achieves 93.53% accuracy on a dataset of 21,780 semantically diverse natural language commands from unseen environments. We run an ablation study to validate the need for different modalities. We also show that a physical robot equipped with the same system without modification can execute 50 semantically diverse natural language commands in both indoor and outdoor environments.**[1]

Fig. 1: Our system grounds spatiotemporal navigation commands in indoor and outdoor environments. The spatial and temporal elements of the example commands are highlighted in blue and red, respectively.

I. Introduction

When giving directions, humans often use natural language that describes goals, as well as temporal and spatial constraints. For example, consider the command "Visit the Starbucks, only then go to the red car to the right of the building, and always avoid the crowded restaurant near the cafe." An autonomous robot following this spatiotemporal command must understand that it specifies a temporally extended task of visiting two locations in a strict order and avoiding the third throughout the execution. The robot must ground the three referring expressions, i.e., "the Starbucks," "the car," and "the crowded restaurant," to specific locations with respect to other landmarks in the environment.

Existing approaches focus on developing the robot's spatial or temporal reasoning ability separately. Many works develop systems to ground natural language commands that contain rich spatial relations in indoor [1, 2, 3] and outdoor [4, 5] environments. A map that contains multimodal semantic information enables robots to identify various target landmarks with respect to others in the environment, yet these approaches cannot handle temporal constraints. Separately, structured task specifications, like linear temporal logic (LTL), can capture a wide range of semantically diverse temporal patterns [6] and enable the synthesis of verifiable robot behaviors with safe guarantees. However, systems that can ground natural language commands with diverse temporal patterns have limited spatial reasoning capability [7, 8].

To achieve the best of both worlds, we introduce a modular system that can ground spatiotemporal navigation commands for robots. Our system uses large language models (LLMs) to recognize spatial referring expressions, like "the red car to the right of the building," and to translate language commands to LTL task specifications, which are compatible with many planning and reinforcement learning algorithms [9, 10, 11, 12, 13]. Using pretrained vision-language models (VLMs) and text embedding, our system grounds referring expressions to specific locations in novel city-scale environments without retraining, given a semantic database of textual and visual descriptions of the landmarks.

We evaluated our language grounding system on a dataset of 21,780 semantically diverse spatiotemporal commands with 1,723 spatial referring expressions and 15 temporal patterns. We also ran an ablation study that shows using multimodal semantic information for spatiotemporal language grounding outperforms using any modality alone. Finally, we demonstrated that a mobile robot equipped with the same system without modification could execute 50 semantically diverse spatiotemporal commands in both indoor and outdoor environments.

II. Preliminaries

A. Large Language Models and Vision-Language Models

Large language models (LLMs) are attention-based neural networks [14] trained to maximize the probability of a successive token given a context window. They achieve the SoTA performance on a wide variety of natural language processing tasks [15]. Pre-trained LLMs can also produce high-dimensional vector embedding of text. We can measure the semantic similarity of two pieces of text by computing the cosine similarity of their embeddings. In this work, we

[1]Videos and supplementary materials are at: `https://spatiotemporal-ground.github.io/`.

used OpenAI's GPT-4 model [16] and the text embedding API for text completion and embedding, respectively, and fine-tuned a T5-base model [17] to translate natural language commands to temporal task specification.

Vision-language models (VLMs) are multimodal models jointly trained on text and images [18]. They have produced SoTA results on many language-conditioned vision tasks [19], e.g., object detection [20, 21], image captioning [22], image retrieval [23], and visual question answering (VQA) [24]. We use GPT-4V(ision) [25] to generate captions for images of landmarks and objects.

B. Temporal Task Specification

Linear temporal logic (LTL) [26] is a promising candidate as a specification language for human-centered specification elicitation [7, 27, 28, 29], and for planning and reinforcement learning [9, 30, 28, 13]. The syntax of LTL is defined through the following recursive grammar:

$$\varphi := \alpha \mid \neg\varphi \mid \varphi_1 \vee \varphi_2 \mid \mathbf{X}\varphi \mid \varphi_1 \ \mathbf{U} \ \varphi_2 \tag{1}$$

Here α represents an atomic Boolean proposition. φ, φ_1, φ_2 are any valid LTL formulas. The operators $\neg$ (not) and $\vee$ (or) are identical to propositional logic operators. The property $\mathbf{X}\varphi$ holds if φ holds at the next time step. The formula $\varphi_1 \ \mathbf{U} \ \varphi_2$ holds if φ_1 holds at least until φ_2 first holds, which must happen at the current or a future time. LTL syntax also admits abbreviated operators defined through the compositions of the primitive operators. In this work, we use the operators $\wedge$ (and), $\mathbf{F}$ (read "finally" or "eventually"), and $\mathbf{G}$ (read "globally" or "always"). $\mathbf{F}\varphi$ specifies that the formula φ must hold at least once in the future while $\mathbf{G}\varphi$ specifies that φ must always hold.

C. Task Execution for Temporal Task Specification

A linear temporal logic (LTL) formula can be transformed to a Büchi automaton [31, 32]. State transitions in the environment induce state transitions in the automaton, so we can track task progress by tracking automaton state transitions. A policy can be computed on the product MDP of the automaton and the environment MDP. Our system is compatible with many planning and reinforcement learning algorithms that solve LTL task specification [9, 10, 33, 11, 12, 13].

III. Problem Definition

Our system receives a user input natural language utterance u that specifies a navigation task in an environment modeled as $\langle \mathcal{S}, \mathcal{A}, T \rangle$, where $\mathcal{S}$ and $\mathcal{A}$ represent the robot's states and actions, and $T(s, a) \rightarrow s'$ captures the transition dynamics. In this work, we consider navigational actions that transition a robot from one location to another in the environment represented as a semantic map. We assume the robot has access to a semantic database $\mathcal{D} = \{p : (z, f)\}$, where p is a proposition that uniquely represents a landmark in the environment, z encodes the semantic information of the landmark, and $f : \mathcal{S} \rightarrow \{0, 1\}$ is a Boolean-valued function that determines the true value of the proposition in a given state. The semantic information of a landmark can be a textual description, including its name, amenity, street address, etc, an image, or both. Our system translates the input command to a linear temporal logic (LTL) formula φ whose propositions are grounded to landmarks in the real world. We assume the robot can track its state in a semantic map and has access to an automated planner that, given an LTL expression as task specification, produces a trajectory in the semantic map. Many planning and reinforcement learning algorithms [9, 10, 11, 12, 13] are compatible with LTL task specification. We use the AP-MDP planner by Oh et al. [11].

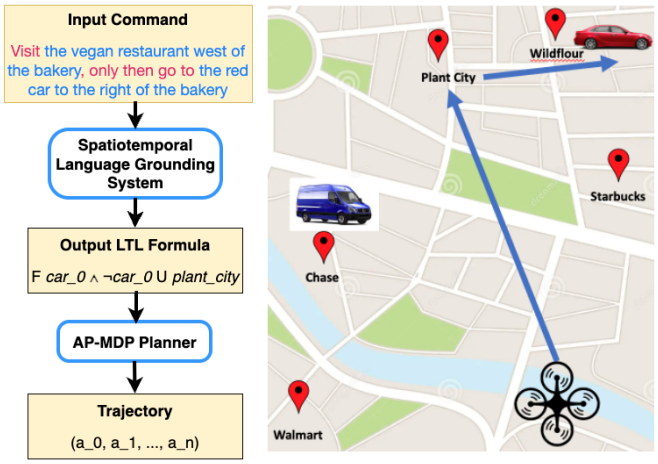


Fig. 2: An example shows an input spatiotemporal navigation command (the spatial and temporal elements are highlighted in blue and red, respectively), an output LTL formula whose propositions are grounded to physical landmarks, and an execution trajectory in the environment.

IV. Spatiotemporal Language Grounding

We approach the problem of spatiotemporal language grounding with a modular design, where we extract spatial referring expressions and translate temporal commands using large language models, as well as ground referring expressions to physical landmarks using a vision-language model and text embedding. Our system produces a grounded temporal task specification incorporating the grounded referring expressions and the spatial relations. Figure 3 shows an overview of the full system.

A. Spatial Referring Expression Recognition (SRER)

The spatial referring expression recognition (SRER) module identifies spatial referring expressions in a given language command. Referring expressions (REs) are noun phrases, pronouns, and proper names that refer to some entity in an environment, such as landmarks and objects [34]. In this work, we only consider noun phrases and proper names and leave the coreference resolution problem to future work. Spatial referring expressions (SREs) are phrases where referring expressions are connected by a spatial relation. For example, in the language command, "Go to the red car to the right of the bakery." The SRE "the red car to the right of the bakery" contains two REs, "the red car" and "the

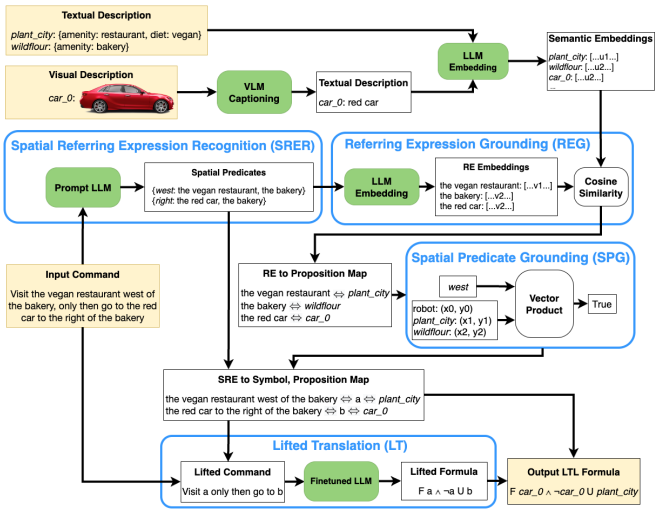


Fig. 3: System Overview: yellow blocks represent the input and output of the system; modules are in blue blocks; green blocks represent pretrained or fine-tuned models.

bakery," termed the figure e_f and the ground e_g, respectively, by Landau and Jackendoff [35]. The figure e_f and the ground e_g are connected by the spatial relation r "in front of." We define a set $\mathcal{R}$ of 19 diverse spatial relations, such as near, in front of, behind, on the left of, on the right of, between, and four cardinal directions. The SRER module extracts referring expressions and their spatial relations from a spatiotemporal language command by prompting an LLM. We use GPT-4 [16]). The output of the SRER module is a spatial predicate denoted by $\{r : (e_f, e_g)\}$. Please see supplementary materials for the prompt used for SRER as well as the complete list of spatial relations.

B. Referring Expression Grounding (REG)

To ground the referring expressions (REs) e_f and e_g to physical landmarks in the environment, we use a multimodal semantic database with textual and visual descriptions of landmarks. We prompt a pretrained vision-language model (VLM) to generate captions of images with the question, "What is the most obvious object in this image?" In this work, we use GPT-4V(ision) [25]. We then use an LLM to generate text embeddings for the image captions, the textual descriptions of landmarks in the semantic database, and the query REs (i.e., e_f and e_g) extracted from the language command. Finally, we use the cosine similarity between text embeddings to find the landmarks that best matches the query REs. The REG module is important for identifying possible candidates for each RE, especially when the environment contains multiple similar landmarks or objects.

We also explored using CLIP's text and image encoders [18] to encode text and images then use cosine similarity of embeddings to find the best matching landmark for a query RE. However, we discovered that the gap between the text and image embedding spaces is large for the pretrained CLIP model. Liang et al. [36] documented this phenomenon in more detail. Instead of training another neural network to align the the text and image embedding spaces, we first use a pretrained VLM to transcribe images to text then work solely in the text embedding space.

C. Spatial Predicate Grounding (SPG)

After grounding the figure e_f and the ground e_g to candidate landmarks, we perform spatial predicate grounding (SPG) to identify the most likely location of the figure given the ground and the spatial relation r. We assume that human users give commands with respect to the robot's initial location. For each spatial referring expression (SRE), we rank all the candidate spatial predicates $\{r : (e_f, e_g)\}$ based on the product of the similarity scores computed by REG for the grounding landmarks of e_f and e_g. To validate each candidate spatial predicate, we first compute a ground vector from e_g to the robot, which serves as an anchor for computing the range where e_f should lie. We then compute a figure vector from e_g to e_f. Depending on the spatial relation, we compute a range where the figure vector should lie based on the ground vector. Figure 4 illustrates the ground and the figure vectors for the SRE "the red car to the right of the bakery."

For each known spatial relation $r \in \mathcal{R}$, we specify a set of rules to validate a pair of candidate figure and ground. In the example of "the red car to the right of the bakery" the spatial relation "to the right of" means the figure vector must lie within the half circle between the ground vector to 180 degrees from the ground vector. Please see supplementary materials for the definition of all spatial relations. We also specify a distance threshold in meters between a figure and the ground to eliminate candidate figures too far from the ground. To resolve an unseen spatial relation, we use LLM text embedding and cosine similarity to find the best matching known spatial relation $r \in \mathcal{R}$.

D. Lifted Translation (LT)

After the SRER module extracts all the spatial referring expressions (SREs) from a given command, we transform it into a lifted command by substituting the SREs with symbols, which are grounded to physical landmarks by the

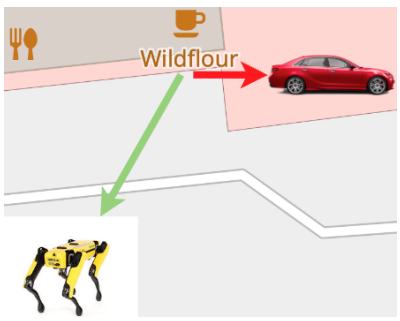


Fig. 4: An illustration of the ground and the figure vectors, depicted as the green and the red arrow, respectively, computed by the spatial predicate grounding (SPG) module (Section IV-C) to resolve the spatial referring expression "the red car to the right of the bakery."

REG (Section IV-B) and the SPG (Section IV-C) modules. For example, the input command "Go to the red car to the right of the bakery" is transformed to a lifted command "Go to a" where the symbol a substitutes the SRE "the red car to the right of the bakery." We then translate the lifted command to a lifted LTL formula compatible with many planning and reinforcement learning algorithms [9, 10, 11, 12, 13]. We evaluate the following models for lifted translation.

Fine-tuned LLM: Liu et al. [8] tested four models that use LLMs for lifted translation. The T5-Base (220M parameters) model [17] fine-tuned on the semantically diverse dataset they collected overperformed the fine-tuned GPT-3 [37], the Prompt GPT-3 [37] and the Prompt GPT-4 [16] models. Thus we use their best performing model fine-tuned T5-Base through HuggingFace's Transformer library [38].

Retrieval Augmented Generation (RAG): We evaluate the method of dynamically constructing a prompt to an LLM based on the query [39] for lifted translation. To translate a lifted command to a lifted LTL formula, we use cosine similarity of text embeddings to find semantically similar commands from the lifted dataset collected in [8], then use these commands and their corresponding LTL formulas as in-context examples to query GPT-4 [16]. We test varying numbers of in-context examples.

V. Evaluation of Language Grounding

We conduct three sets of evaluation of our spatiotemporal language grounding system: 1) a modular evaluation, where we test the performance of individual modules introduced in Section IV; 2) a full system evaluation, where we evaluate the final output of our system; and 3) an ablation study of the text and the image modalities.

A. Dataset

Our evaluation uses four city-scale environments with an increasing number of landmarks, i.e., 9, 34, 44, and 175. The landmarks are described by text from OpenStreetMap [40] (e.g., names, street addresses, amenities, and GPS coordinates, etc.) and images from Google StreetView [41]. Having landmarks described by both modalities helps evaluate if the referring expression grounding (REG) module can use a proper modality to correctly ground referring expressions to landmarks.

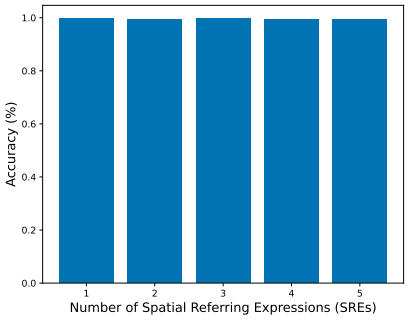
To obtain semantically diverse spatiotemporal navigation commands, we first collect 1,723 spatial referring expressions (SREs) with respect to the robot's initial location from human users, then substitute the SREs in the 1,089 lifted natural language commands provided by [8]. The lifted commands cover 15 temporal patterns for common robotic tasks, each with 20 to 38 lifted commands. For example, given the lifted command "Walk to a then to b", we can substitute the symbols a and b with the SREs "the vegan restaurant west of the bakery" and "the red car," respectively, to obtain the grounded natural language command "Walk to the vegan restaurant west of the bakery, then to the red car." We construct 21,780 unique spatiotemporal language commands using five seeds to sample SREs for substitution. The commands contain varying numbers of SREs ranging from one to five.

B. Modular Evaluation

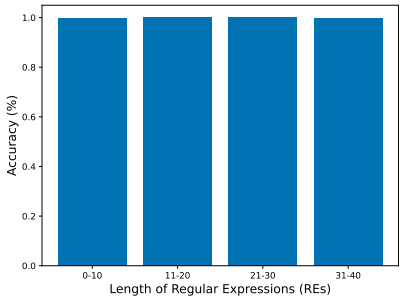
We first evaluate each module introduced in Section IV on the semantically diverse dataset introduced in Section V-A. All results are averaged over five seeds.

Spatial Referring Expression Recognition (SRER): We evaluate the LLM's ability to extract the correct number of spatial referring expressions (SREs) from a natural language command and correctly identify their structures described in Section IV-A, i.e., $\{r : (e_f, e_g)\}$ with the spatial relation r, the figure e_f and the ground e_g. As shown in Table I, the SRER module can reliably recognize SREs and their corresponding spatial predicates in language commands from unseen environments. Figure 5a further demonstrates that SRER achieves nearly perfect performance across commands with varying numbers of SREs. Occasionally, when a language command contains five SREs of large lengths, the SRER module may fail to parse an SRE to the correct spatial predicate.

Referring Expression Grounding (REG): We evaluate the ability of the REG module to ground referring expressions, i.e., figures and grounds, to the correct physical landmarks described by text and images in the semantic map. We observe in Table I that the Top-1 accuracy decreases



(a) SRER Accuracy vs. Utterance Complexity



(b) REG Accuracy vs. RE Complexity

Fig. 5: Figure 5a shows the accuracies of the spatial referring expression recognition (SRER) module as the complexity of utterances (measured by the number of SREs in an utterance) increases. Figure 5b shows the accuracy of the referring expression grounding (REG) module as the complexity of REs (measured by string length) increases.

TABLE I: Modular Performance

Module		Accuracy				
		City 1 (9 landmarks)	*City 2* (34 landmarks)	*City 3* (44 landmarks)	*City 4* (175 landmarks)	*Average*
SRER		$99.45 \pm 0.12\%$	$99.43 \pm 0.26\%$	$99.56 \pm 0.63\%$	$99.39 \pm 0.21\%$	$99.46 \pm 0.34\%$
REG	Top-1	$99.68 \pm 0.72\%$	$97.98 \pm 1.07\%$	$88.74 \pm 2.14\%$	$78.35 \pm 1.97\%$	$91.19 \pm 8.84\%$
	Top-5	$100.00 \pm 0.00\%$	$100.00 \pm 0.00\%$	$99.56 \pm 0.24\%$	$99.15 \pm 0.34\%$	$99.68 \pm 0.41\%$
	Top-10	$100.00 \pm 0.00\%$	$100.00 \pm 0.00\%$	$99.70 \pm 0.17\%$	$99.98 \pm 0.05\%$	$99.92 \pm 0.15\%$
SPG		$100.00 \pm 0.00\%$	$100.00 \pm 0.00\%$	$99.53 \pm 0.33\%$	$99.35 \pm 1.46\%$	$99.72 \pm 0.75\%$
LT	T5	$99.45 \pm 0.00\%$	$99.45 \pm 0.00\%$	$99.45 \pm 0.00\%$	$99.45 \pm 0.00\%$	$99.45 \pm 0.00\%$
	RAG-10	$69.33 \pm 0.25\%$	$70.34 \pm 0.13\%$	$69.65 \pm 0.58\%$	$70.39 \pm 0.84\%$	$69.93 \pm 0.62\%$
	RAG-50	$83.79 \pm 0.06\%$	$83.93 \pm 0.12\%$	$83.75 \pm 0.52\%$	$83.93 \pm 0.65\%$	$83.85 \pm 0.33\%$
	RAG-100	$88.20 \pm 0.58\%$	$88.25 \pm 1.04\%$	$87.79 \pm 0.39\%$	$87.70 \pm 0.13\%$	$87.98 \pm 0.54\%$

as the number of landmarks increases from City 1 to City 4. With more landmarks, there are more instances from the same category that share similar textual or visual features. For example, there may be multiple cafe shops or red bicycles in a large environment. However, as we increase the number of top candidates from 1 to 10, the REG module achieves nearly perfect performance. Since REG provides candidate groundings of figures and grounds to the SPG module (evaluated next), we hypothesize that as long as the correct landmark is among the top candidates, our system can still ground to the correct landmarks. We use ten as the number of candidate groundings for REG. Figure 5b shows that as the complexity of REs increases, the REG module consistently achieves near-perfect Top-10 accuracies. These results align with that reported by Liu et al. [8].

Spatial Predicate Grounding (SPG): Our evaluation of the SPG module assesses whether the correct figure landmarks can be identified using the spatial reasoning described in Section IV-C. As shown in Table I, SPG performs uniformly well across all environments. The few failure cases are due to instances where the figure and the ground landmarks are far apart, and a closer landmark is available to serve as the ground landmark.

Lifted Translation (LT): We compare the accuracies of the best-performing model in Liu et al. [8], i.e., T5-base fine-tuned on a large composted dataset, and retrieval augmented generation (RAG) [39] with varying numbers of in-context examples. Fine-tuned T5-base model achieves high accuracies across all environments, which means the composed dataset constructed by [8] covers most temporal patterns we consider in this work. For RAG, we vary the number of in-context examples from 10 to 100, the maximum number of tokens allowed by GPT-4 [16]. We observe that as the number of examples increases, the accuracy increases but is lower than that of the fine-tuned T5 model. Thus, we use the fine-tuned T5-base model for lifted translation in the full system. For cost effective reasons, we average the RAG results over two seeds per city.

C. Full System Evaluation and Ablation Study

We test the overall performance of our language grounding system that takes a spatiotemporal navigation command as input and produces an LTL formula whose propositions are grounded to physical landmarks in the environment. To evaluate the effectiveness of multimodality semantic information for language grounding, we conduct an ablate study where we only use one modality, i.e., text or images, in the referring expression grounding (REG) module.

The full system using both modalities significantly outperforms the image-only system because images alone often do not provide enough information, especially when there are distractor objects. It outperformed the text-only system by more than 10%. The margin is much smaller than that with the image-only system because our full system essentially uses textual description to ground REs after converting images to text. Still, the additional visual features provided by images can further disambiguate similar landmarks. For example, colors can help disambiguate a red and a yellow bicycle. In reality, detailed textual descriptions of landmarks are not always available, e.g., "the red brick building," but can be easily extracted from images by querying a pretrained VLM for suitable image captions. The accuracy of the spatial predicate grounding (SPG) module when given the top-10 candidate groundings from the referring expression grounding (REG) module is $97.26 \pm 2.07\%$. It supports our hypothesis that if the correct RE grounding is among the top candidates, SPG can identify the correct figure landmark based on spatial reasoning.

Note that the text-only system is the same as Lang2LTL [8]. Liu et al. [8] showed that Lang2LTL outperforms Code-as-Policies [42], a prominent system that grounds natural language instructions to Python code directly executable on robots.

VI. Robot Demonstration

To demonstrate the ability of our language grounding system to execute spatiotemporal commands, we deploy the same system without modification at the task planning level on a quadruped robot Spot [43] in an indoor and an outdoor environment. They contain nine and five objects, respectively, with multiple objects and landmarks that have similar textual or visual features, e.g., tables, couches, buildings, dumpsters, and cars.

We use Spot's GraphNav software to build a semantic map of the environment and capture images of landmarks and objects of interest. For the outdoor environment, we

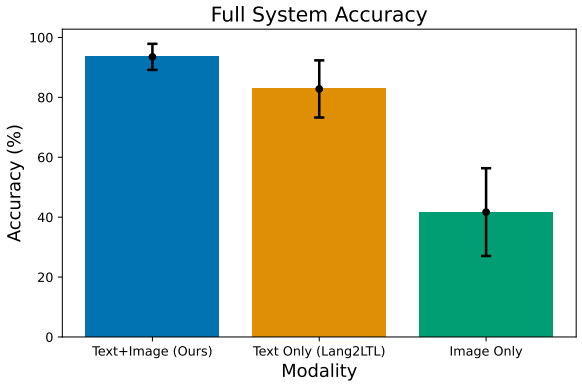


Fig. 6: This graph depicts the average accuracies of spatiotemporal language grounding systems using different modalities across four environments and five seeds for each environment.

additionally download textual descriptions of landmarks in the region from OpenStreetMap [40]. We only use images for indoor experiments. Given a grounded LTL task specification output by our language grounding system, we use the AP-MDP planner [11] to produce a sequence of actions that traverse the semantic map. We execute 50 semantically diverse spatiotemporal natural language commands on the physical robot. With the formal safety guarantee offered by AP-MDP planner for LTL task specification, the robot is able to abort the execution, if a given task is infeasible. Please see supplementary materials for the complete list of commands.

VII. Related Work

A. Grounding Spatial Commands for Robots

SLOOP [3] is a system that grounds spatial commands in partially observable environments by using the spatial relations between a target object and multiple landmarks to construct an initial belief for a POMDP planner. LanguageRefer [44] is a learned transformer-based model that takes as inputs a spatial language command, a 3D point cloud of the scene, and bounding boxes of objects, then predicts the target object. RoboHop [45] builds a topological map of the environment with image segments as nodes. Like our work, RoboHop uses an LLM to extract referring expressions (REs) from a language command. Then it uses a VLM to ground REs to nodes in the topological map.

B. Grounding Temporal Commands for Robots

Linear temporal logic (LTL) [26] is a mathematically precise language that can specify robotic tasks and provide satisfaction guarantees, especially for long-horizon, temporally-extended tasks. Early work of using LTL for temporal command grounding was limited to structured language [46]. Gopalan et al. [7] trained a Seq2Seq network [47] on natural language and LTL pairs in every new environment to ground language commands for navigation and manipulation. Like our work, Berg et al. [27] and Hsiung et al. [48] first translated commands to lifted LTL formulas then grounded the propositions to landmarks or objects but used a Seq2Seq network with limited capabilities.

To mitigate the lack of training data, Pan et al. [49] used an LLM to paraphrase structured language commands constructed from algorithmically generated LTL formulas. Patel et al. [50] and Wang et al. [51] proposed weakly supervised methods that use executed trajectories instead of LTL annotations to guide language grounding. Similarly, Lang2LTL [8] is a modular system that uses LLMs to ground temporally extended navigation commands in indoor and outdoor environments without retraining, given a text-based semantic database. However, Lang2LTL cannot ground spatial referring expressions or landmarks with visual descriptions. Our system improves upon Lang2LTL by incorporating spatial reasoning and using a vision-language model (VLM) to process images.

C. Grounding Spatiotemporal Commands for Robots

Language commands from existing works of indoor [1, 2, 3, 52] and outdoor [4, 5] navigation are rich in spatial relations, but lack diverse temporal patterns. Our system considers language commands containing 15 temporal patterns commonly used in robotics [6]. LM-Nav [5] uses an LLM to extract a sequence of referring expressions (REs) from a navigation command, then a VLM to ground the REs to images of physical landmarks. LM-Nav only grounds language commands of sequenced visit type defined in [6]. VLMaps [53] fuses pretrained vision-language features with depth information to construct a spatial map of the environment then directly indices a sequence of spatial referring expressions (SREs) extracted by an LLM in the map. LIMP [52] uses an LLM and a VLM in a similar way as LM-Nav. In addition, it uses RGB-D information to construct a 3D scene representation for motion planning to solve indoor mobile manipulation tasks. LIMP grounds language commands of three temporal patterns. An additional advantage of our system is its ability to ground REs that are not easily represented by images, e.g., "the vegan restaurant," by using the textual description from OpenStreeMap [40] and resolving city-scale navigation commands.

VIII. Conclusion

We propose a modular system that consists of pretrained large language models and a pretrained vision-language model to ground spatiotemporal navigation commands to landmarks described by text and images in a semantic map of novel indoor and outdoor environments. We evaluate the individual modules and the full language grounding system on a semantically diverse dataset of 21,780 spatiotemporal navigation commands in novel city-scale environments. Our system achieves 93.53% accuracy outperforming the previous SoTA. An autonomous robot with access to a semantic map and position tracking can use the same system without modification to follow spatiotemporal navigation commands in novel indoor and outdoor environments. We envision incorporating interaction with human users to further improve spatiotemporal language grounding.

REFERENCES

[1] P. Anderson, Q. Wu, D. Teney, J. Bruce, M. Johnson, N. Sünderhauf, I. Reid, S. Gould, and A. Van Den Hengel, "Vision-and-Language Navigation: Interpreting visually-grounded navigation instructions in real environments," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018, pp. 3674–3683.

[2] A. Ku, P. Anderson, R. Patel, E. Ie, and J. Baldridge, "Room-Across-Room: Multilingual vision-and-language navigation with dense spatiotemporal grounding," in *Conference on Empirical Methods for Natural Language Processing (EMNLP)*, 2020.

[3] K. Zheng, D. Bayazit, R. Mathew, E. Pavlick, and S. Tellex, "Spatial Language Understanding for Object Search in Partially Observed City-scale Environments," in *2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN)*. IEEE, 2021, pp. 315–322.

[4] H. Chen, A. Suhr, D. Misra, N. Snavely, and Y. Artzi, "Touchdown: Natural Language Navigation and Spatial Reasoning in Visual Street Environments," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019, pp. 12 538–12 547.

[5] D. Shah, B. Osiński, S. Levine *et al.*, "LM-Nav: Robotic Navigation with Large Pre-Trained Models of Language, Vision, and Action," in *Conference on Robot Learning (CoRL)*. PMLR, 2023, pp. 492–504.

[6] C. Menghi, C. Tsigkanos, P. Pelliccione, C. Ghezzi, and T. Berger, "Specification Patterns for Robotic Missions," *IEEE Transactions on Software Engineering*, vol. 47, no. 10, pp. 2208–2224, oct 2021.

[7] N. Gopalan, D. Arumugam, L. L. Wong, and S. Tellex, "Sequence-to-Sequence Language Grounding of Non-Markovian Task Specifications," in *Robotics: Science and Systems (RSS)*, 2018.

[8] J. X. Liu, Z. Yang, I. Idrees, S. Liang, B. Schornstein, S. Tellex, and A. Shah, "Grounding Complex Natural Language Commands for Temporal Tasks in Unseen Environments," in *Conference on Robot Learning (CoRL)*. PMLR, 2023, pp. 1084–1110.

[9] M. L. Littman, U. Topcu, J. Fu, C. Isbell, M. Wen, and J. MacGlashan, "Environment-Independent Task Specifications via GLTL," *arXiv preprint arXiv:1704.04341*, 2017.

[10] A. Camacho, R. T. Icarte, T. Q. Klassen, R. A. Valenzano, and S. A. McIlraith, "LTL and Beyond: Formal Languages for Reward Function Specification in Reinforcement Learning," in *IJCAI*, vol. 19, 2019, pp. 6065–6073.

[11] Y. Oh, R. Patel, T. Nguyen, B. Huang, E. Pavlick, and S. Tellex, "Planning with State Abstractions for Non-Markovian Task Specifications," in *Robotics: Science and Systems (RSS)*, vol. 2019, 2019.

[12] R. T. Icarte, T. Q. Klassen, R. Valenzano, and S. A. McIlraith, "Reward Machines: Exploiting Reward Function Structure in Reinforcement Learning," *Journal of Artificial Intelligence Research*, vol. 73, pp. 173–208, 2022.

[13] J. X. Liu, A. Shah, E. Rosen, M. Jia, G. Konidaris, and S. Tellex, "Skill Transfer for Temporally-Extended Task Specifications," *2024 IEEE International Conference on Robotics and Automation (ICRA)*, 2024.

[14] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. u. Kaiser, and I. Polosukhin, "Attention Is All You Need," in *Advances in Neural Information Processing Systems*, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds., vol. 30. Curran Associates, Inc., 2017.

[15] A. Radford, J. Wu, R. Child, D. Luan, D. Amodei, I. Sutskever *et al.*, "Language Models are Unsupervised Multitask Learners," *OpenAI blog*, vol. 1, no. 8, p. 9, 2019.

[16] OpenAI, "GPT-4 Technical Report," 2023, accessed the model on March 18, 2024.

[17] C. Raffel, N. Shazeer, A. Roberts, K. Lee, S. Narang, M. Matena, Y. Zhou, W. Li, and P. J. Liu, "Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer," *Journal of Machine Learning Research*, vol. 21, no. 140, pp. 1–67, 2020.

[18] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, G. Krueger, and I. Sutskever, "Learning Transferable Visual Models From Natural Language Supervision," in *Proceedings of the 38th International Conference on Machine Learning*, ser. Proceedings of Machine Learning Research, M. Meila and T. Zhang, Eds., vol. 139. PMLR, 18–24 Jul 2021, pp. 8748–8763.

[19] J. Zhang, J. Huang, S. Jin, and S. Lu, "Vision-Language Models for Vision Tasks: A Survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pp. 1–20, 2024.

[20] T. Lüddecke and A. Ecker, "Image Segmentation Using Text and Image Prompts," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2022, pp. 7086–7096.

[21] M. Minderer, A. Gritsenko, A. Stone, M. Neumann, D. Weissenborn, A. Dosovitskiy, A. Mahendran, A. Arnab, M. Dehghani, Z. Shen *et al.*, "Simple Open-Vocabulary Object Detection," in *European Conference on Computer Vision*. Springer, 2022, pp. 728–755.

[22] J. Chen, H. Guo, K. Yi, B. Li, and M. Elhoseiny, "VisualGPT: Data-Efficient Adaptation of Pretrained Language Models for Image Captioning," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2022, pp. 18 030–18 040.

[23] Z. Liu, C. Rodriguez-Opazo, D. Teney, and S. Gould, "Image Retrieval on Real-Life Images With Pre-Trained Vision-and-Language Models," in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, October 2021, pp. 2125–2134.

[24] Y. Du, J. Li, T. Tang, W. X. Zhao, and J.-R. Wen, "Zero-shot visual question answering with language model feedback," in *Findings of the Association for Computational Linguistics: ACL 2023*. Association for Computational Linguistics, Jul. 2023, pp. 9268–9281.

[25] Z. Yang, L. Li, K. Lin, J. Wang, C.-C. Lin, Z. Liu, and L. Wang, "The Dawn of LMMs: Preliminary Explorations with GPT-4V(ision)," *arXiv preprint arXiv:2309.17421*, 2023.

[26] A. Pnueli, "The Temporal Logic of Programs," in *18th Annual Symposium on Foundations of Computer Science (sfcs 1977)*. ieee, 1977, pp. 46–57.

[27] M. Berg, D. Bayazit, R. Mathew, A. Rotter-Aboyoun, E. Pavlick, and S. Tellex, "Grounding Language to Landmarks in Arbitrary Outdoor Environments," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 208–215.

[28] A. Shah, S. Li, and J. Shah, "Planning with Uncertain Specifications (PUnS)," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 3414–3421, 2020.

[29] A. Shah, P. Kamath, S. Li, P. Craven, K. Landers, K. Oden, and J. Shah, "Supervised Bayesian Specification Inference from Demonstrations," *The International Journal of Robotics Research*, vol. 42, no. 14, pp. 1245–1264, 2023.

[30] R. T. Icarte, T. Klassen, R. Valenzano, and S. McIlraith, "Using Reward Machines for High-Level Task Specification and Decomposition in Reinforcement Learning," in *International Conference on Machine Learning*. PMLR, 2018, pp. 2107–2116.

[31] M. Y. Vardi, "An Automata-Theoretic Approach to Linear Temporal Logic," *Logics for Concurrency*, pp. 238–266, 1996.

[32] R. Gerth, D. Peled, M. Y. Vardi, and P. Wolper, "Simple On-the-fly Automatic Verification of Linear Temporal Logic," in *Protocol Specification, Testing and Verification XV: Proceedings of the Fifteenth IFIP WG6. 1 International Symposium on Protocol Specification, Testing and Verification, Warsaw, Poland, June 1995*. Springer, 1996, pp. 3–18.

[33] G. De Giacomo, L. Iocchi, M. Favorito, and F. Patrizi, "Foundations for Restraining Bolts: Reinforcement Learning with LTLf/LDLf Restraining Specifications," in *Proceedings of the International Conference on Automated Planning and Scheduling*, vol. 29, 2019, pp. 128–136.

[34] J. Lyons, *Semantics: Volume 2*. Cambridge University Press, 1977, vol. 2.

[35] B. Landau and R. Jackendoff, ""What" and "where" in spatial language and spatial cognition," *Behavioral and Brain Sciences*, vol. 16, pp. 217–265, 06 1993.

[36] V. W. Liang, Y. Zhang, Y. Kwon, S. Yeung, and J. Y. Zou, "Mind the Gap: Understanding the Modality Gap in Multi-modal Contrastive Representation Learning," *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 35, pp. 17 612–17 625, 2022.

[37] T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei, "Language Models are Few-Shot Learners," in *Advances in Neural Information Processing Systems*, vol. 33, 2020, pp. 1877–1901.

[38] T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, P. Cistac, T. Rault, R. Louf, M. Funtowicz, J. Davison, S. Shleifer, P. von Platen, C. Ma, Y. Jernite, J. Plu, C. Xu, T. L. Scao, S. Gugger, M. Drame, Q. Lhoest, and A. M. Rush, "Transformers: State-of-

the-Art Natural Language Processing," in *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, Oct. 2020, pp. 38–45.
[39] P. Lewis, E. Perez, A. Piktus, F. Petroni, V. Karpukhin, N. Goyal, H. Küttler, M. Lewis, W.-t. Yih, T. Rocktäschel *et al.*, "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks," *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 33, pp. 9459–9474, 2020.
[40] O. Contributors, "Planet OSM," https://www.openstreetmap.org, 2017.
[41] D. Anguelov, C. Dulong, D. Filip, C. Frueh, S. Lafon, R. Lyon, A. Ogale, L. Vincent, and J. Weaver, "Google Street View: Capturing the World at Street Level," *Computer*, vol. 43, no. 6, pp. 32–38, 2010.
[42] J. Liang, W. Huang, F. Xia, P. Xu, K. Hausman, B. Ichter, P. Florence, and A. Zeng, "Code as policies: Language model programs for embodied control," in *arXiv preprint arXiv:2209.07753*, 2022.
[43] Boston Dynamics, "Spot® - The Agile Mobile Robot," https://www.bostondynamics.com/products/spot.
[44] J. Roh, K. Desingh, A. Farhadi, and D. Fox, "LanguageRefer: Spatial-Language Model for 3D Visual Grounding," in *Conference on Robot Learning (CoRL)*. PMLR, 2022, pp. 1046–1056.
[45] S. Garg, K. Rana, M. Hosseinzadeh, L. Mares, N. Suenderhauf, F. Dayoub, and I. Reid, "RoboHop: Segment-based Topological Map Representation for Open-World Visual Navigation." IEEE, 2024.
[46] H. Kress-Gazit, G. E. Fainekos, and G. J. Pappas, "From Structured English to Robot Motion," in *2007 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2007, pp. 2717–2722.
[47] I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to Sequence Learning with Neural Networks," *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 27, 2014.
[48] E. Hsiung, H. Mehta, J. Chu, J. X. Liu, R. Patel, S. Tellex, and G. Konidaris, "Generalizing to New Domains by Mapping Natural Language to Lifted LTL," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 3624–3630.
[49] J. Pan, G. Chou, and D. Berenson, "Data-Efficient Learning of Natural Language to Linear Temporal Logic Translators for Robot Task Specification," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023.
[50] R. Patel, E. Pavlick, and S. Tellex, "Grounding Language to Non-Markovian Tasks with No Supervision of Task Specifications," in *Robotics: Science and Systems (RSS)*, vol. 2020, 2020.
[51] C. Wang, C. Ross, Y.-L. Kuo, B. Katz, and A. Barbu, "Learning a natural-language to LTL executable semantic parser for grounded robotics," in *Conference on Robot Learning (CoRL)*. PMLR, 2021, pp. 1706–1718.
[52] B. Quartey, E. Rosen, S. Tellex, and G. Konidaris, "Verifiably Following Complex Robot Instructions with Foundation Models," *arXiv preprint arXiv:2402.11498*, 2024.
[53] C. Huang, O. Mees, A. Zeng, and W. Burgard, "Visual Language Maps for Robot Navigation," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 10 608–10 615.