LOP-Field: Brain-inspired Layout-Object-Position Fields for Robotic Scene Understanding

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Abstract

Spatial cognition empowers animals with remarkably efficient navigation abilities, largely depending on the scene-level understanding of spatial environments. Recently, it has been found that a neural population in the postrhinal cortex of rat brains is more strongly tuned to the spatial layout rather than objects in a scene. Inspired by the representations of spatial layout in local scenes to encode different regions separately, we proposed LOP-Field that realizes the Layout-Object-Position(LOP) association to model the hierarchical representations for robotic scene understanding. Powered by foundation models and implicit scene representation, a neural field is implemented as a scene memory for robots, storing a queryable representation of scenes with position-wise, object-wise, and layout-wise information. To validate the built LOP association, the model is tested to infer region information from 3D positions with quantitative metrics, achieving an average accuracy of more than 88%. It is also shown that the proposed method using region information can achieve improved object and view localization results with text and RGB input compared to state-of-the-art localization methods.

1 Introduction

Spatial cognition is a fundamental function that enables humans and animals to achieve long-term autonomy in their environment. A cognitive map is considered a mental representation of spatial information about the relative locations and attributes of phenomena in our everyday spatial environment [1]. Place cells encode the specific locations of rodents in the environment depending on both scene content and spatial layout [2]. Spatial view cells in the hippocampus become active when scene contents of the environment are in the animal's field of view [3]. Various boundary cells [4, 5, 6, 7] encode the allocentric scene border whatever the scene contents are. A particular population of neurons in the postrhinal cortex (POR) is more sensitive to the spatial layout of a local scene than the spatial contents [8]. A theory of geometry representations is proposed to describe various boundary-related cells and representations of POR in a unified framework. The predicted

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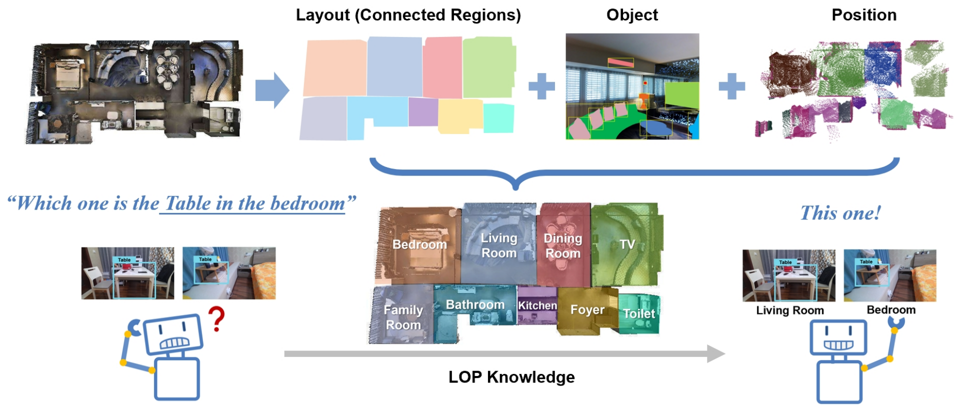


Figure 1: Dividing the scene information into layout, object, and position, and modeling them explicitly, layout-object-position association enables robots to address relative problems and realize a more comprehensive spatial cognition.

geometry cells by the theory are able to encode spatial layouts with different geometric structures, which helps to quickly form a high-level cognitive map representation [9]. The spatial layout, connected by regions, may play a vital role in spatial cognition, reasoning, and navigation, integrating with the purpose of the scene and object content semantics.

Inspired by neural representations of spatial layout, scene contents, and locations, spatial information can be categorized into (1) layout-level information, which includes the layout, region, and connectivity of spaces, (2) object-level information, which includes the attributes, appearance, and positions of various objects, and (3) position-level information, which includes the relative positions, associations, and modes of interaction among object parts. For example, people can distinguish different regions within their homes, recognizing the differences between the living room, bedroom, and kitchen. They can build knowledge and memories about the relationship between target objects (e.g., bed) and their corresponding regions (e.g., bedroom), and they can distinguish similar objects within different regions (e.g., a cup in the living room versus a cup in the kitchen). Similarly, if a robot could understand the relationships between spatial regions as humans do, it would be able to perform tasks such as spatial reasoning and layout-object associations. Fig. 1 shows that with layout-object-position association, robots could have enhanced spatial cognition and understanding capabilities.

In robotics research on spatial scene understanding, current efforts have yielded impressive results in tasks such as 3D environment reconstruction[10, 11, 12, 13, 14, 15], object detection[16, 17, 18, 19, 20], and object segmentation[21, 22, 23, 24, 25, 26]. However, most of these works have focused on producing lifelike scene reconstructions and precise geometric and semantic information about objects, with relatively few studies addressing the modeling and recognition of spatial layouts, such as scene regions, and the association with spatial contents. The lack of layout information and scalable association in scenes hinders a robot's comprehensive understanding and makes it difficult to interpret related commands.

How to enable robots to learn about spatial regions and association with contents remains a challenging problem, however, recent advances in large foundation models offer potential solutions. Large foundation models trained on massive datasets across various scenes, such as vision-language models(VLMs) like CLIP[27] and large language models(LLMs) like Sentence-BERT[28], are believed to have the ability to reason with general knowledge and perform zero-shot inference on multiple tasks. Numerous studies leverage these models to process visual-textual features of scenes, establishing links between spatial coordinates and these features. For instance, works like CLIP-Fields[29] and VLMaps[30] establish mappings between spatial positions and object visual-language features, while GARField[31] proposes hierarchical segmentation and grouping, dividing scenes into different physical scales. These efforts facilitate linking object features to 3D positions, but most existing research does not establish region recognition and lacks the integration of layout-object-position information.

To effectively integrate spatial layouts, scene objects, and position information, we introduce the LOP-Field, which realizes the Layout-Object-Position (LOP) association to model the hierarchical representations for robotic scene understanding. It integrates the spatial layout connected by regions and object-level semantics with context on 3D positions. It is equipped with the ability to reason about the relationship between the regions of the scene and its content, thus enhancing the object-level 3D reasoning capabilities of the previous work. Such a neural field can serve as a scene memory for robots, storing a queryable representation of scenes with hierarchical LOP information. By inputting RGB-D sequences, the LOP-Field is optimized using a contrast loss between its predicted features and features from the VLM and LLM, resulting in little need for annotation. To validate the established LOP relationship, we conducted experiments on several multi-room apartment scenes. We evaluated the model's ability to infer region information from 3D positions, providing quantitative metrics. We also demonstrated improved object and view localization results using object-region relations with text and RGB inputs. These experiments conclusively prove that LOP-Field effectively associates information of layout and scene contents from different scales.

Our contributions can be listed as follows:

- Inspired by the recent significant findings in neuroscience, we propose a neural scene representation named LOP-Field that integrates spatial layouts, scene objects, and 3D positions for robotic scene understanding.
- By fusing the object information from detected objects and layout region information from background contexts, LOP-Field builds layout-object-position association in a neural scene representation to match the vision-language and semantic feature space of large foundation models with little need for annotation.
- Various experiments are conducted to validate the layout-object-position association. LOP-Field achieves an accuracy of more than 95% on region inference using 3D positions and we demonstrate the help of scalable information association in downstream object and image localization tasks.

2 Related Works

2.1 Spatial Understanding with Layout Information

Understanding the mechanisms of spatial cognition in humans has been a challenging and active areas of cognitive science, which also serves as an important reference for enabling robots with scene understanding. During decades of research, scientists have made great efforts to understand the mechanism of spatial cognition. A mental representation of spatial information is proposed to describe the relative locations and attributes of phenomena in our everyday spatial environment, called a cognitive map. Place cells, as the embodiment of the cognitive map, encode the specific locations of rodents in the environment depending on both scene content and spatial layout [2]. Scene content of the environment is represented by spatial view cells in the hippocampus, while Various boundary cells [4, 5, 6, 7] encode the allocentric scene boundary regardless of the scene content. Recently, Patrick et al.[8] showed that a population code in the POR is more strongly tuned to the spatial layout than to the content in a scene. The firing activities remain consistent even when the environmental content and lighting conditions change. This suggests that there are specialized cells and signaling mechanisms to process layout in the process of scene understanding, which captures the spatial layout of complex environments to rapidly form a high-level cognitive map representation [9]. We propose that the spatial layout connected by regions, as a high-level abstract semantic feature, is closely related to the object contents and purposes of the scene, and therefore it can establish connections with object semantics more easily than other layout information such as area, volume, and boundary. However, the layout regions of the scene and their association with scene content have received little attention in current robotics research on scene understanding.

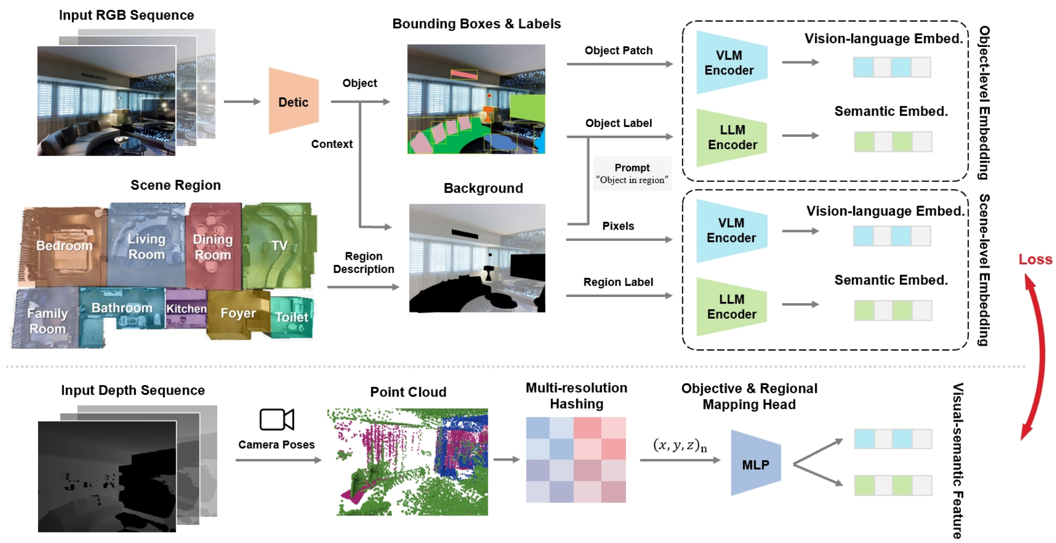
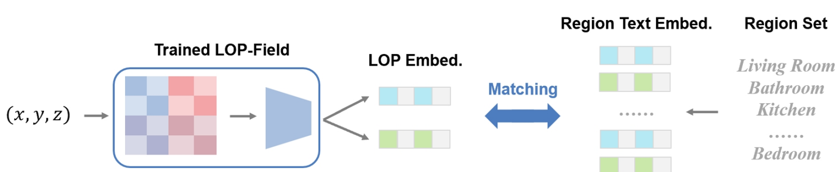
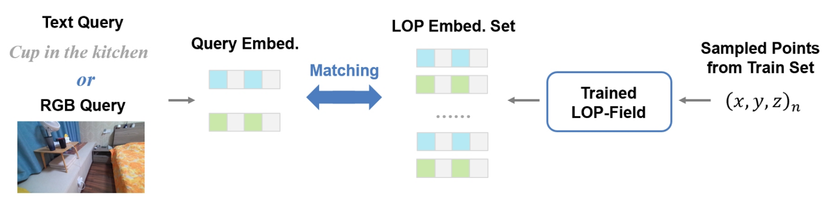


Figure 2: Pipeline of the target embedding processing and neural implicit rendering during training. Above is the ground truth generation of layout-object-position vision-language and semantic embeddings for weakly-supervising. Below is the neural implicit network mapping 3D positions to target feature space. A contrastive loss is optimized against each other.



(a) Region inference with position inputs



(b) Localization with text and image queries

Figure 3: The application examples pipeline of the LOP-Field. The region inference using position input is shown in (a). The LOP association helped localization of text and image query is shown in (b).

2.2 Neural Scene Representation

Traditional robotic scene recognition methods, such as multi-view synthesis[32, 33, 34, 35] and grid-based scene representation[36, 37], aim to reconstruct realistic new views and predict complete geometry and appearance information. However, approaches based on reprojection losses struggle to obtain sufficient constraints for optimization, and voxel-based representations face challenges when scaling to large-scale or high-resolution scenes. To address these issues, NeRF (Neural Radiance Fields)[38] introduced a novel approach that uses implicit neural fields to represent scene information. Subsequently, numerous efforts have been made to improve the training and inference speed of neural rendering fields[39, 40, 41, 42, 43], to adapt them to larger scenes[44, 45, 46], and to explore extended application scenarios[47, 48, 49]. A popular research direction is to integrate high-dimensional information, such as semantics, with NeRF to achieve a more comprehensive understanding of scenes and to address a wider range of downstream tasks[50, 51, 52]. However, training accurate

NeRF models that incorporate semantic information requires costly manual annotation and presents challenges in adapting and applying them to different scenes.

2.3 Large Foundation Model Powered Scene Understanding

Recently, several robotics works have utilized large foundation models trained on web-image data to assist in the understanding of semantic information in scenes. These works have demonstrated that models trained on web-image data can be used for self-supervised learning. Seal[53] employed a detection model trained on web-image data to establish the connection between semantics and 3D voxels. Cliport[54] and [55] achieved scene understanding using weakly supervised models trained on web-image data, leveraging techniques such as CLIP[27]. Huy Ha et al.[56] utilized CLIP features to annotate 3D points in space. CLIP-Fields[29] and VLMaps[30] directly train an implicit representation of a scene using visual-linguistic features, establishing correspondence between 3D spatial points and semantics. However, the semantic feature field learned in the above methods represents object semantics and does not include scene-level features. In contrast, in our work, CLIP[27] and Sentence-BERT[28] are used to generate vision-linguistic and semantic features for objects, spatial regions, and contexts, respectively. In addition to using object semantics generated by back-projection for 3D points in the scene, we annotate the belonging regions of 3D points based on spatial layout and regional division of scenes. Such annotations incur minimal cost but establish connections between the position of 3D points, object semantics, and scene regions.

3 Method

In this section, we first elaborate on the problem formulation of how to associate layout regions, object semantics, and 3D positions. We provide examples of the usage of LOP association, like region inference from positions and downstream localization tasks. Next, we present the process of generating the target features for training. Furthermore, we explain the structure of the employed implicit scene representation. Lastly, we describe the training procedures.

3.1 Problem Formulation

3.1.1 Foundation-Model-Based Neural Implicit Representation

Our goal is to learn an implicit representation of a scene by establishing associations between 3D positions and their corresponding layout regions and object features. Therefore, we need to design a scene-dependent implicit function, denoted as

$$F : \mathbb{R}^3 \to \mathbb{R}^n,$$

where for any point P in space, $F(P)$ represents the layout-object-position associated features of that point. CLIP[27] is introduced as the VLM in this work to encode the object and region information, integrating the vision and language feature space. Besides, the Sentece-BERT[28] feature is also introduced in this work. Because intuitively, unlike objects that can have similar appearances within a certain category, region information often lacks specific visual appearances and is closely related to semantic representations like the integration purpose of the scene and object semantics. Models trained on large-scale question-answering datasets can aid in understanding the semantic relationships between regions and objects. Consequently, $\mathbb{R}^n$ stands for embeddings:

$$\mathcal{E} = \{(e_v, e_s)\}$$

including vision-language embedding e_v and semantic embedding e_s in our approach. These predicted implicit representation outputs are targeted to match the features from the pre-trained CLIP[27] C and Sentence-BERT[28] S separately.

3.1.2 Target Feature Processing

To get the target layout-object-position features, RGB-D image sequences with poses are accepted as input, what's more, for pure RGB image sequences, depth point clouds and camera poses estimated through methods like COLMAP[57] or simultaneous localization and mapping(SLAM) can also be used. For each image I, we employ Detic[58] D as the detection model to generate bounding-box-constrained object patches $B = \{b_1, b_2, \ldots, b_i\}$ and labels $L = \{l_1, l_2, \ldots, l_i\}$, followed by CLIP[27] and Sentence-BERT[28] to process the vision-language and semantic features. Given the related region r_P and object instance o_P of point P, P can be labeled with $\{C(b_P), S(o_P, r_P)\}$, where the text prompt is formed as o_P *in* r_P. What's more, the background appearance is also considered which we proposed to include context information for region layout. For background pixel Q out of the object masks, its related region $r_Q \in R = \{r_1, r_2, \ldots, r_m\}$ is regarded as the text label and its label can be calculated as $\{C(Q), S(r_Q)\}$. To obtain region labels of image pixels, we back-project them to 3D space based on depth and simply consider the top-down view of the 3D point cloud. The space can be partitioned into different regions using walls as dividers. Consequently, the target feature space processed by foundation models can be denoted as

$$\mathcal{F} = \{(f_v, f_s)\},$$

where f_v is the visual-language feature from CLIP[27] and f_s is the semantic feature from Sentence-BERT[28]. The processing pipeline is shown in Fig. 2.

3.1.3 Layout-Object-Position Association

With the function and feature representation mentioned above, we can infer the region information and utilize it for various downstream tasks.

Region Inference. Using spatial 3D point P_i as input, assuming a collection of space regions R, we compute the vision-language features $\mathcal{C}_R = \{C(r_1), C(r_2), \ldots, C(r_m)\}$ and semantic features $\mathcal{S}_R = \{S(r_1), S(r_2), \ldots, S(r_m)\}$. Then the similarity between $\mathcal{E}_{P_i} = \{(e_v, e_s)\}$ and $\{\mathcal{C}_R, \mathcal{S}_R\}$ is calculated to find the most likely region to which P_i belongs. The inference process is shown in Fig. 3.

LOP Guided Object Localization. For text input t, such as "cup in the bedroom," most existing robotic scene representations struggle to locate specific objects of interest (differentiating between cups in the living room and the bedroom, for example). However, with our proposed LOP-Field that includes scene region information, we can calculate the similarity between $\{\mathcal{C}_t, \mathcal{S}_t\}$ and the embeddings $\mathcal{E}_{P^*}$ of the sampled point P^* set from the scene. Compared with previous object localization methods, $\mathcal{E}_{P^*} = \{(e_v, e_s)\}$ includes contexts between region layout and objects by considering the object information of detected objects and region information of the background appearance.

LOP Guided View Localization. Another common robotic application is to localize a captured image of the scene. Unlike previous methods that only encode the object semantics to find matches, LOP-Field introduces region features to constrain the prediction. For image input I, the similarity of $\{\mathcal{C}_I, \mathcal{S}_I\}$ with $\mathcal{E}_{P^*} = \{(e_v, e_s)\}$ is calculated. Compared to previous methods that only encode objects, the text label of object point P is formed as o_P *in* r_P(e.g., cup in the kitchen), and the background appearance with region label is also encoded. These all contribute to a more accurate localization of a specific image view. The localization of both text query and image query is shown in Fig. 3.

3.2 Model Architecture

Our proposed LOP-Field involves an implicit mapping function to encode the 3D positions and separate head processing encodings to match the target feature space. To select an appropriate implicit function, considering that the target feature space includes object-level local features and layout-level region feature representation, we employ the Multi-scale Hierarchical Encoding (MHE) introduced in Instant-NGP[59]. The feature pyramid structure used in MHE allows for considering structural features ranging from coarse to fine in the spatial domain. Additionally, MHE has a faster training speed compared to traditional NeRF[38] network structures. For mapping the position encodings to the target feature space, we employ a unified and simple Multi-Layer Perceptron(MLP)

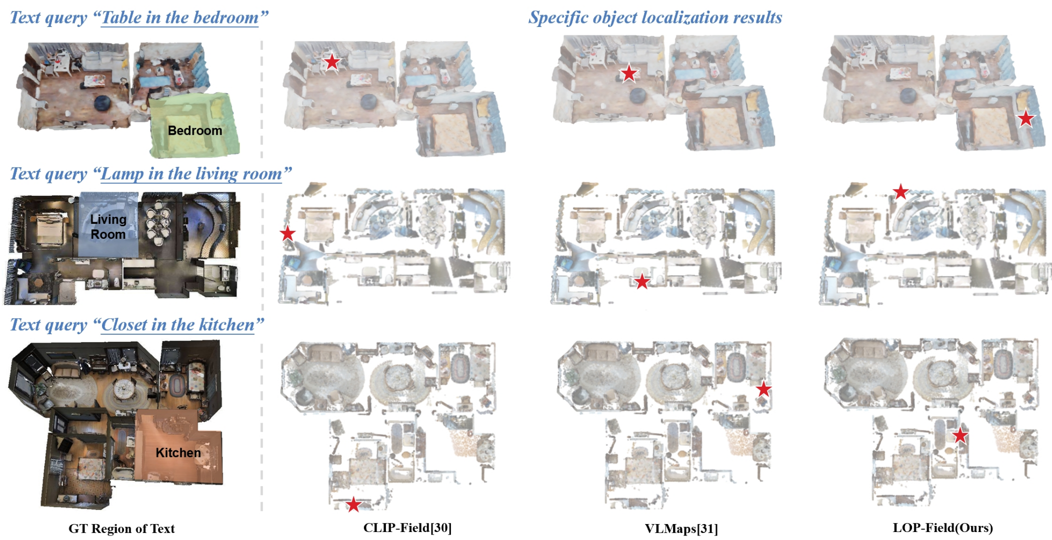


Figure 4: The object localization results among state-of-the-art methods and our method with text input in the form of *object in the region*. Red stars show the position of the found results of input texts.

network structure. It includes heads $head_v$ for obtaining vision-language features and $head_s$ for semantic features. The model for training is shown in Fig. 2.

3.3 Training

The pipeline of ground truth data generation is described in Section 3.1.2. To fit the multiple embeddings generated by the implicit representation introduced in Section 3.1.1 to the target feature space, we design the loss function through a contrastive approach. For the vision-language feature optimization, the tempered similarity matrix on point P is denoted as

$$\text{Sim}_v = \tau e_v C(P),$$

where τ is the temperature term. Using cross-entropy loss, the vision-language loss can be calculated as

$$\mathcal{L}_v = -e^{-\text{dist}_P}(H(\text{Sim}_v) + H(\text{Sim}_v{}^T)),$$

where dist_P is the distance from P to camera, and H is the cross-entropy function. For the semantic loss, similarity on object points P_o and background points P_b can be calculated as

$$\text{Sim}_s^{P_o} = \tau e_s S(o_{P_o}, r_{P_o}),\ \text{Sim}_s^{P_b} = \tau e_s S(r_{P_b}).$$

Similarly, semantic loss can be denoted as

$$\mathcal{L}_s = -\text{conf}(H(\text{Sim}_s) + H(\text{Sim}_s{}^T)),$$

where $conf$ is the prediction confidence from the detection model. The total loss is computed by:

$$\mathcal{L} = \mathcal{L}_v + \mathcal{L}_s.$$

In our experiments, an NVIDIA RTX3090 GPU is utilized and the batch size is set to 12544 to maximize the capability of our VRAM. The MHE has 18 levels of grids and the dimension of each grid is 8. We train the neural implicit network for 100 epochs with a decayed learning rate of $1e-4$. Each epoch contains $3e6$ samples.

4 Experimental Results

To validate the established layout-object-position relationship of LOP-Field, we designed the following experiments related to region information in scenes. Our experimental data consists of multi-room

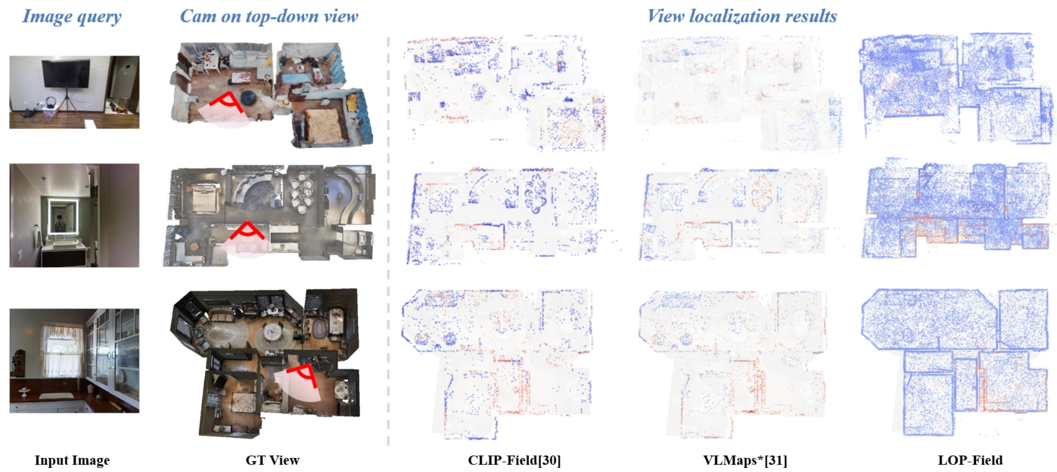


Figure 5: The image localization heatmaps among state-of-the-art methods and our method with text input in the form of *object in the region*. Red lines and the sector represent the field of view region.

Regions	Scene1			Scene2			Scene3			Scene4		
	Acc.	Pre.	F1	Acc.	Pre.	F1	Acc.	Pre.	F1	Acc.	Pre.	F1
Living Room	0.948	0.970	0.959	0.870	0.881	0.875	0.778	0.810	0.793	0.902	0.949	0.925
Bedroom	0.943	0.825	0.880	0.925	0.923	0.924	0.687	0.767	0.725	0.920	0.870	0.894
Bathroom	0.466	0.680	0.554	0.903	0.898	0.901	0.875	0.463	0.605	0.797	0.831	0.814
Dining Room	-	-	-	0.961	0.794	0.870	0.774	0.732	0.752	0.933	0.887	0.910
Lobby	0.681	0.941	0.790	0.853	0.951	0.899	0.978	0.510	0.671	0.855	0.698	0.769
Family Room	-	-	-	-	-	-	0.903	0.571	0.700	0.926	0.936	0.931
Kitchen	0.994	0.654	0.789	0.788	0.836	0.811	0.833	0.833	0.833	0.758	0.854	0.803
Office	-	-	-	0.969	0.848	0.905	-	-	-	0.953	0.883	0.917
Toilet	-	-	-	-	-	-	0.900	0.711	0.795	-	-	-
Avg. Acc./Samples	0.886 / 169k			0.900 / 185k			0.884 / 111k			0.894 / 112k		

Table 1: Region prediction results on the test set of different scenes from the Matterport3D[60] dataset. Accuracy, precision, and F1 score are used as metrics.

environment from Matterport3D[60] as well as apartment environment[48], which allows us to demonstrate that our approach can be generalized in diverse scenarios. The data environment is of single-floor residential buildings which is the common working scenario of household robots widely studied in this field.

4.1 Region Inference

To demonstrate the built LOP association integrates positions with layout, we designed experiments that accept 3D positions as input to infer the region information. For quantitative evaluation, we divided the RGB-D sequences of data into training and testing sets. The LOP-Field is trained according to Section 3.3 on the training set and tested with data from the test set. As the region inference task can be treated as a multi-class classification task for each input, the accuracy, precision, and F1-score are used as metrics. Tab. 4.1 shows the region inference results. It can be seen that in multi-region environments with different scales and layouts, the average accuracy exceeds 88%. This experiment demonstrates that the implicit representation of the scene can successfully establish the connection between 3D points and their corresponding region features.

4.2 LOP Guided Localization

Text Input Object Localization: For objects of the same category existing in multiple regions, we input the textual description of the target object in the form of "object in the region" and infer the specific location of the target, comparing the results with the predictions of current state-of-the-art visual-language algorithms. Fig. 4 demonstrates the advancements of LOP-Field in object localization tasks involving region information, which allows for the localization of specific target objects based on the description and features of the region, while other methods confuse objects from different regions. We tested over 160 text queries on 4 scenes of Apartment[48] and Matterport3D[60] dataset. The accuracy of LOP-Field to localize the specific objects in the target regions exceeds 90%, while other methods have a significant fluctuation in accuracy. More results can be seen in the appendix.

Image Input View Localization: To validate the help of region information in the image view localization task. We localize the images from the test set in the trained LOP-Field. The localization results are shown in Fig. 5 in the form of heatmaps. VLMaps* is a self-implemented version, because origin VLMaps[30] does not implement the image localization task. To align with CLIP-Field[29] and our work, the LSeg[61] used in VLMap[30] is replaced by CLIP[27]. The results show that LOP-Field constrains the localization results to a smaller range in the exact region. We sampled more than 40 images on each of the 4 scenes from Apartment[48] and Matterport3D[60] dataset. By drawing the predicted camera view on the top-down view, we estimated the localization precision and found that almost all views can be ranged into a specific view on the target field of view, while other methods struggle to get precise results.

5 Conclusion and Limitations

Inspired by neural representations of spatial layout, scene contents, and locations, this paper proposed the LOP field, an implicit scene representation field that associates layout-object-position information, powered by foundation models for robotic scene understanding. Our experiments show that with the help of LOP association, region inference ability and better results in several downstream tasks are achieved. However, due to time and page constraints, this study explored only a very limited application of scalable associative information. In addition, the accuracy of the model decreases when distinguishing between regions with similar functions (such as living room, family room, and TV room). Furthermore, we currently lack a good method to model the confidence of the predicted results when presented with images that do not contain representative objects (with sufficient information to infer the region) or with degraded visual features.

We will investigate how the layout-object-position association information can be effectively used to perform challenging tasks that previously relied solely on the semantic information of the objects. Examples of such tasks include complex environment relocalization problems, reasoning about logical relationships between regions and objects, and efficient navigation between different regions. We believe that the integration of layout-object-position can significantly enhance a robot's spatial perception capabilities and encourage researchers to pay attention to the encoding of scene-specific information.

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A Appendix / supplemental material

A.1 Scene Partation Example

The scene can be partitioned into different regions using walls as dividers and lines can be aligned to these walls. This is similar in most scenarios, making the annotation of scene regions a straightforward task as shown in Fig. A1.

A.2 Vision-language Embeddings Similarity of Region and Objects

To demonstrate that the relationship of the vision-language and semantic embeddings for different regions is related to our intuition, we compare the similarity in region-region and object-region form and show the results in Fig. A2. It can be seen that based on general knowledge, cognitively related regions(e.g., the dining room and kitchen) and object-region pairs(e.g., sink and kitchen) are also more correlated in the vision-language and semantic feature spaces.

A.3 Ablation Study

To explicitly encode the region information, we apply the LVM to process the background pixels out of the object bounding box and LLM to encode the region label text. What's more, for object pixels, object label text is combined with the region text in the form of 'object in the region' before being encoded by LLM.

Source of Region Information. In our very initial version, we assume that objects with region text include enough information to encode region layouts rather than encoding the background appearance. The region embeddings completely come from the region text label, and object embeddings are learned separately. Fig. A3 shows the difference in embedding processing between the initial version and the current method. Ablation results in Fig. A4 show that context and layout information in background pixels is necessary for layout-object-position association.

Vision-language and Semantic Embeddings Weight. To ablate the contribution of vision-language embeddings from CLIP and semantic embeddings from Sentence-BERT in encoding region features, we compare different weight settings between the v-s embeddings when inferring the regions with 3D position inputs. Results are shown in Fig. A4. It can be seen that both vision-language embeddings and semantic embeddings are indispensable, and weight settings with the greatest results are used for LOP-Field.

A.4 Additional Experiment Results

Additional experiments results of object localization using text query inputs and view localization using image query inputs.

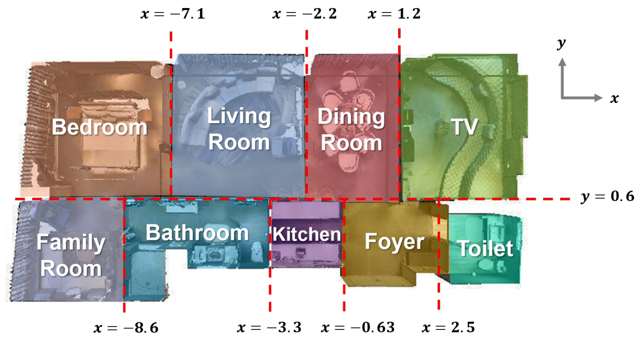
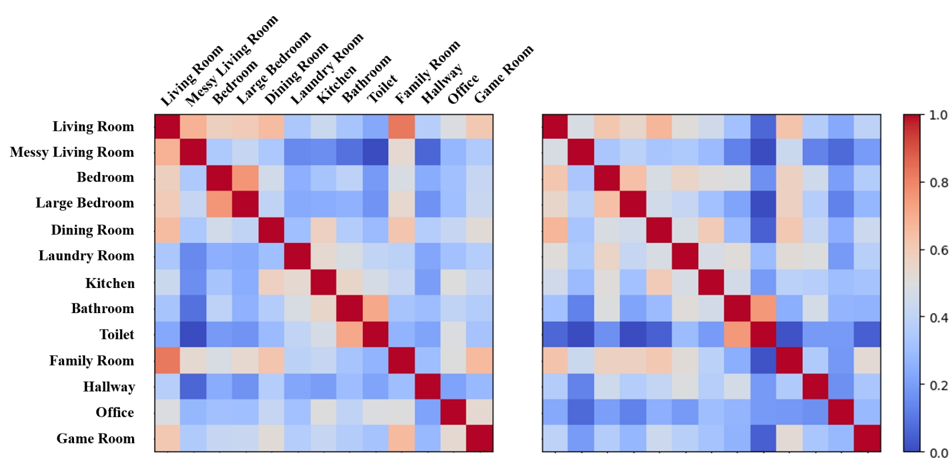
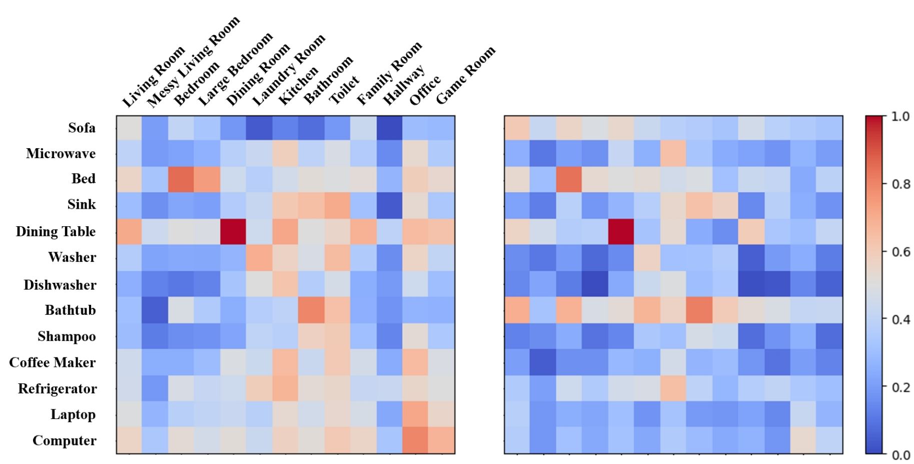


Figure A1: Using walls as dividers to associate lines with them, the scene can be divided into various regions and 3D points can be labeled with related regions easily.



(a)



(b)

Figure A2: The similarity of a set of region embeddings(as shown in a) and object-region embeddings(as shown in b). The left graph shows the vision-language embedding similarity and the right one shows the semantic embedding similarity.

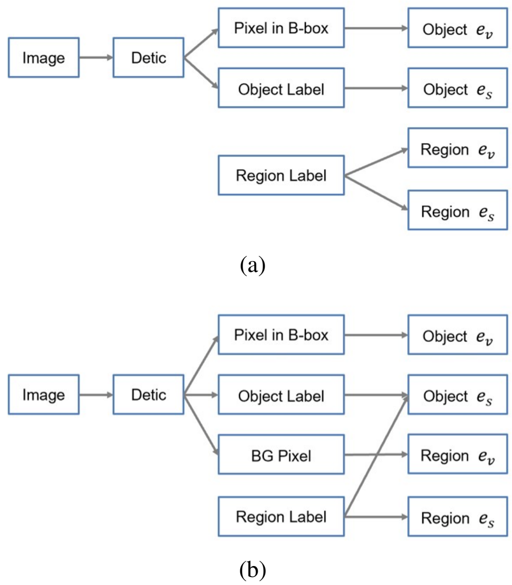


Figure A3: The different source of region information. The initial version which encodes regions from text description is shown in (a), and the current method which encodes background context is shown in (b).

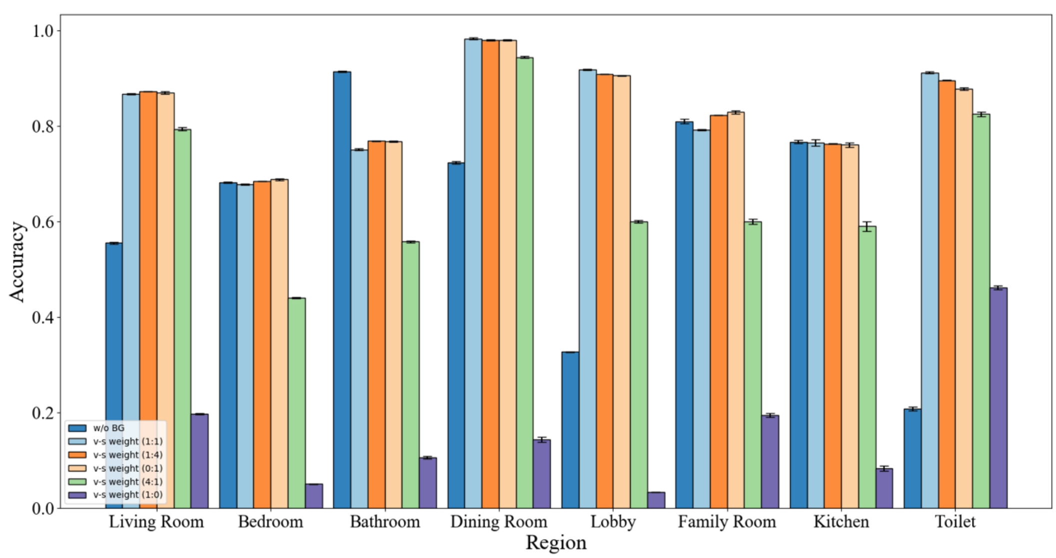


Figure A4: Ablation results on the accuracy of region prediction on Matterport3D[60] with 3D positions input. The w/o BG stands for not encoding background pixels to get region embeddings, and v-s weight ablates the weight of vision-language and semantic embeddings in the embeddings similarity contribution. Error bars show the results among samples from different scenes in Matterport3D[60].

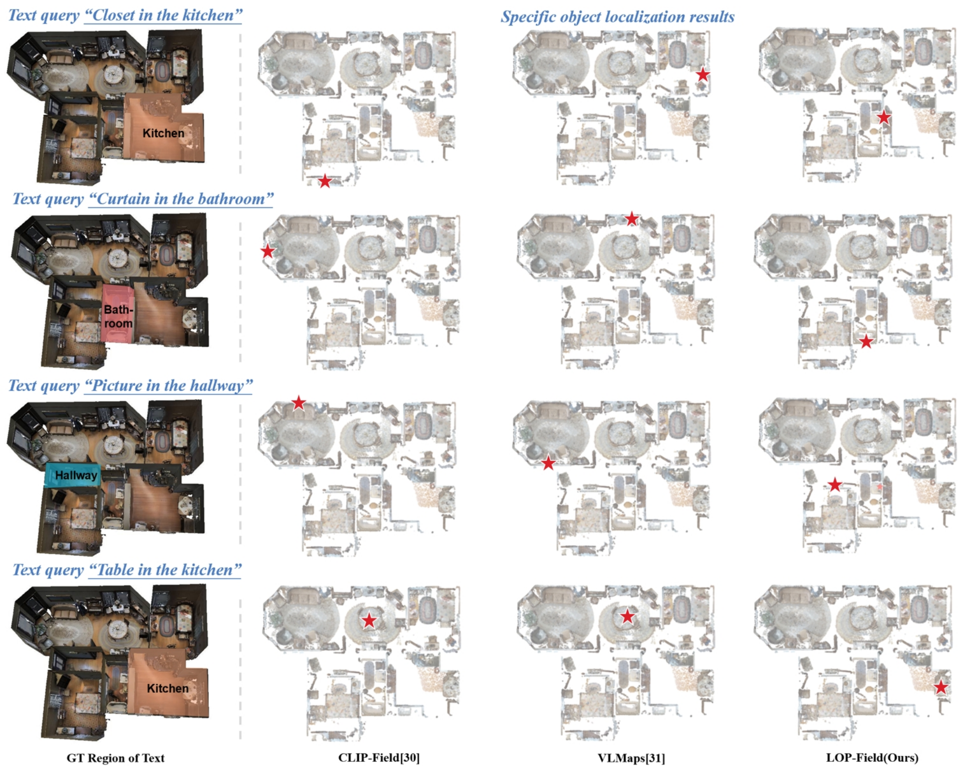


Figure A5: Text query localization on scene 2t7WUuJeko7[60].

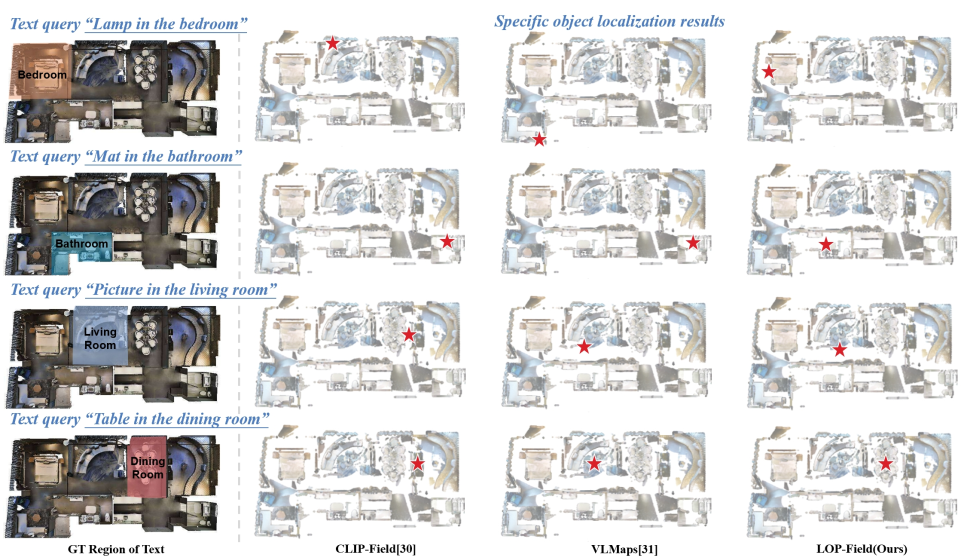


Figure A6: Text query localization on scene 17DRP5sb8fy[60].

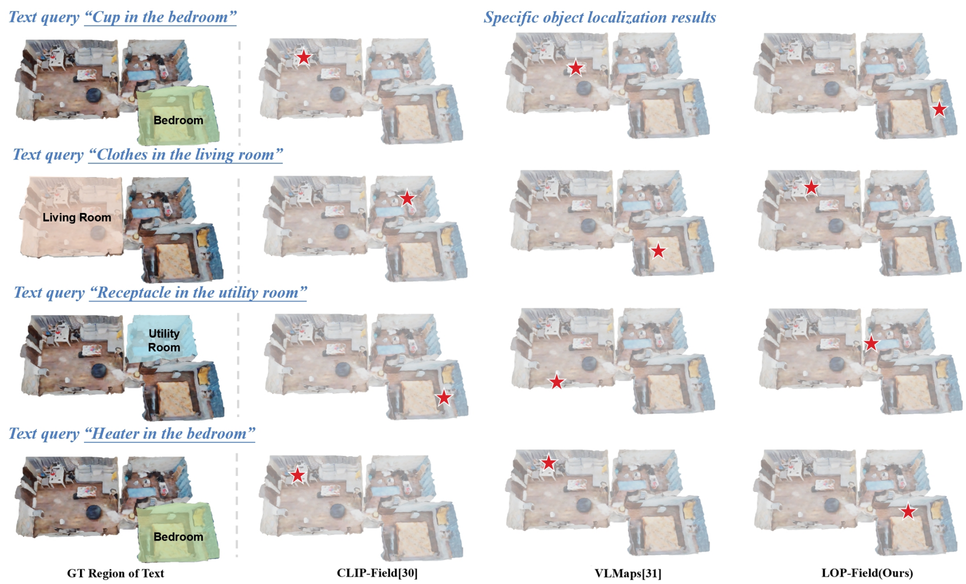


Figure A7: Text query localization on scene Apartment[48].

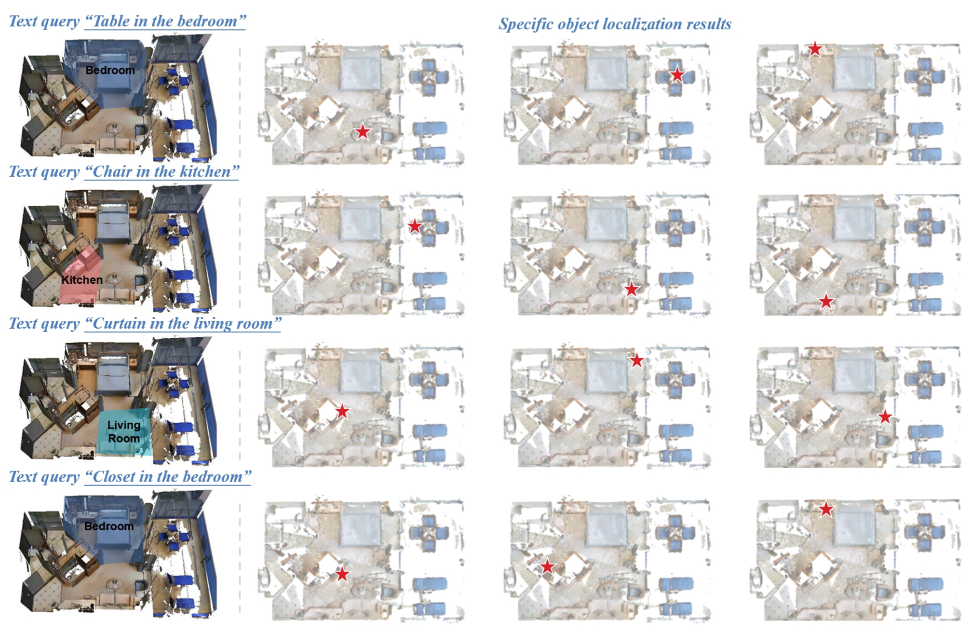


Figure A8: Text query localization on scene HxpKQynjfin[60].

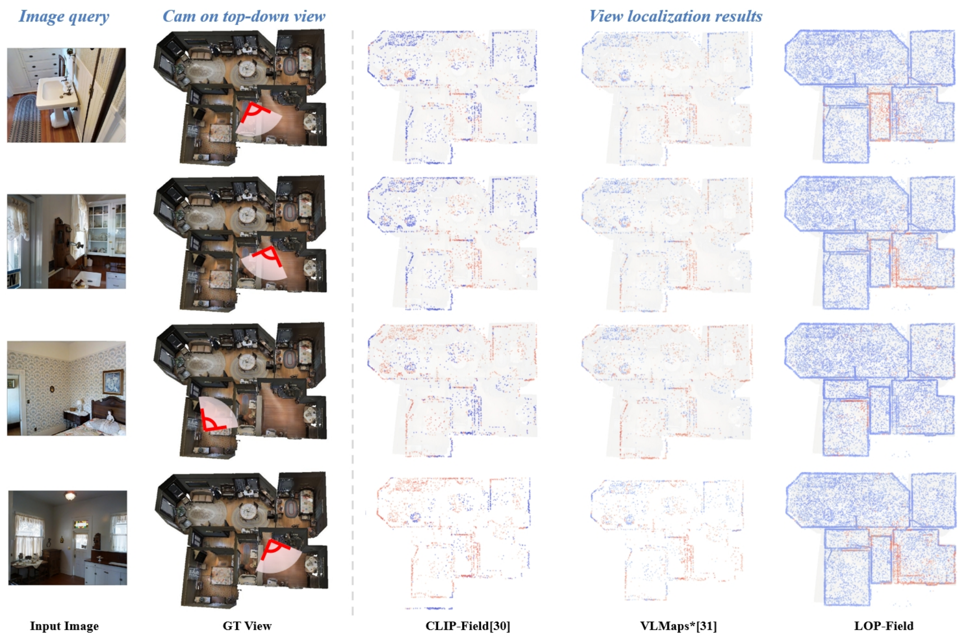


Figure A9: Image query localization on scene 2t7WUuJeko7[60].

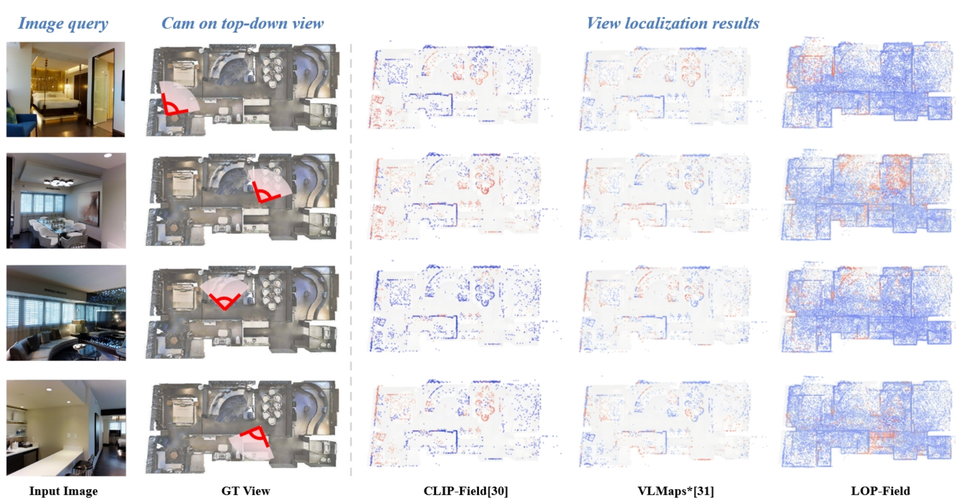


Figure A10: Image query localization on scene 17DRP5sb8fy[60].

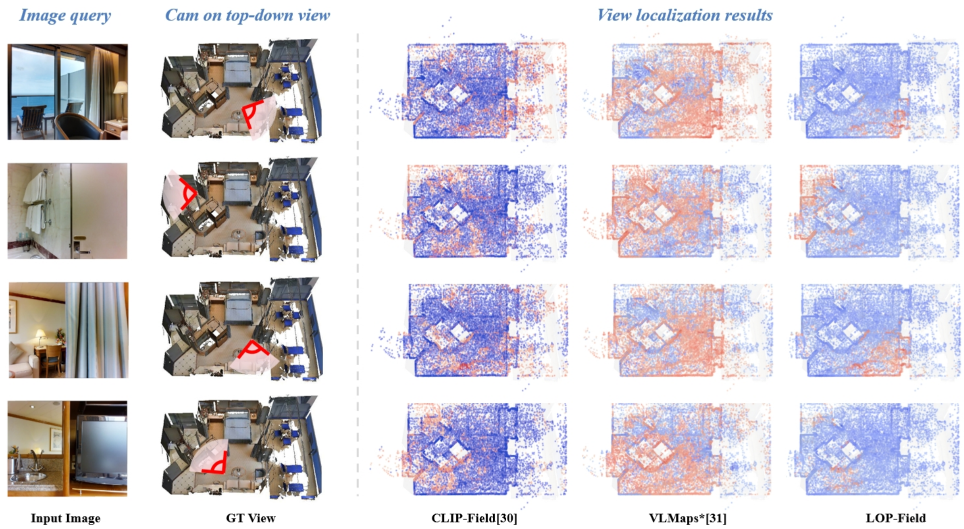


Figure A11: Image query localization on scene HxpKQynjfin[60].

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