

Situational Awareness Matters in 3D Vision Language Reasoning

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Abstract

Being able to carry out complicated vision language reasoning tasks in 3D space represents a significant milestone in developing household robots and human-centered embodied AI. In this work, we demonstrate that a critical and distinct challenge in 3D vision language reasoning is the situational awareness, which incorporates two key components: (1) The autonomous agent grounds its self-location based on a language prompt. (2) The agent answers open-ended questions from the perspective of its calculated position. To address this challenge, we introduce SIG3D, an end-to-end Situation-Grounded model for 3D vision language reasoning. We tokenize the 3D scene into sparse voxel representation, and propose a language-grounded situation estimator, followed by a situated question answering module. Experiments on the SQA3D and ScanQA datasets show that SIG3D outperforms state-of-the-art models in situational estimation and question answering by a large margin (e.g., an enhancement of over 30% on situation accuracy). Subsequent analysis corroborates our architectural design choices, explores the distinct functions of visual and textual tokens, and highlights the importance of situational awareness in the domain of 3D question-answering. Project page is available at <https://yunzeman.github.io/situation3d>.

1. Introduction

Humans learn knowledge efficiently through the interactions with the 3D world and the integration of multi-modal information, such as verbal guidance or instructions. Similarly, introducing language guidance into the visual comprehension task can greatly enhance models’ learning efficiency [3, 42]. Nonetheless, despite considerable advancements in linguistic understanding [7, 11, 31, 58] and vision-language integration [3, 37, 54, 61], current methodologies remain deficient in accurately perceiving and rationalizing within real-world 3D environments, which is largely attributed to the lack of 3D situational reasoning capabilities.

Compared with machine learning models, humans put

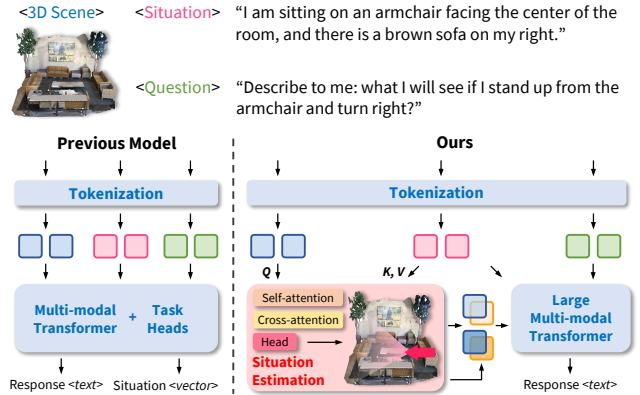


Figure 1. Previous methods perform direct 3D vision language reasoning without modeling the situation of an embodied agent in the 3D environment. Our method, SIG3D, grounds the situational description in the 3D space, and then re-encodes the visual tokens from the agent’s intended perspective before vision-language fusion, resulting in a more comprehensive and generalized 3D vision language (3DVL) representation and reasoning pipeline. Q, K, V stands for query, key, and value, respectively.

themselves inside the 3D world and then perceive and interact with the surrounding environment from their ego-perspective (Figure 1). Such situational awareness is a crucial difference between 2D and 3D visual understanding, and a key to achieve seamless understanding of spatial concepts in more complex real-world environments. Several existing methods recognize the lack of positional understanding in 3D and propose new benchmarks and joint optimization functions [44], or positional embedding methods [26] to enhance the overall reasoning performance.

However, the lack of an *explicit* situation modeling and situation-grounded 3D reasoning method restricts them from obtaining a generalizable and consistent 3D vision-language (VL) representation. As shown in Figure 2, the situation prediction of the state-of-the-art method [44] (in blue) diverges significantly from the ground truth vectors (in red) in almost all scenes in the dataset [13]. Moreover, our pilot study in Section 3 also reveals that situational understanding, despite being very crucial in comprehending the context of questions, only plays a minor role in the final

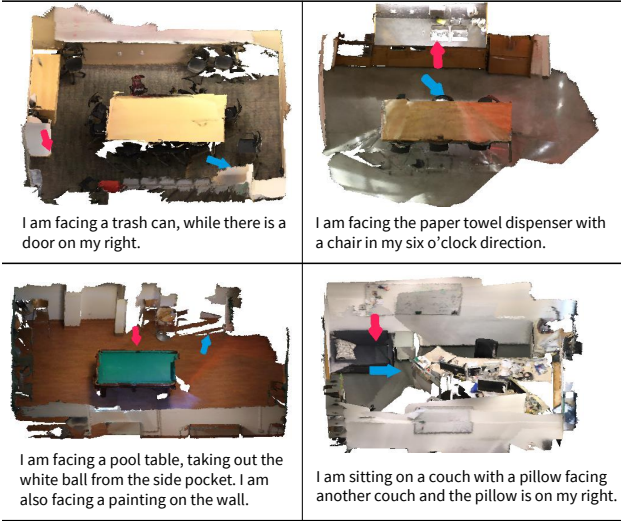


Figure 2. Situational estimation in existing methods [44] fails in most scenarios, indicating the missing registration between the situational description and 3D embeddings. **Red**: Ground truth (GT) vector. **Blue**: Estimated vector.

question-answering performance of existing methods.

In this work, we propose SIG3D, a novel approach designed to *precisely model and estimate an embodied agent’s ego-location and orientation from a textual description*, before performing multi-modal QA tasks from the agent’s egocentric perspective, as shown in Figure 1. Specifically, we leverage large-scale pretrained language and visual encoders to process the input text and 3D data, and fuse the tokens with attention modules to predict a situational vector. Previous attempts to directly predict the ego-situation are hindered by the expansive search space inherent in 3D environments. To address this challenge, we re-conceptualize the task as an *anchor-based classification*, where visual tokens are regarded as anchor points, and a likelihood of position together with a set of rotation parameters are concurrently regressed for each visual token. After obtaining the situational estimation, we propose a situational alignment and a situation-guided token re-encoding strategy, to perceive the environment from the agent’s intended perspective. These strategies enhance the visual token with more accurate situational awareness for subsequent QA tasks.

Experiments on two challenging 3D visual question-answering (VQA) datasets [5, 44] demonstrate the significant improvement on situational estimation and QA tasks of our model. In particular, we improve the situational estimation accuracy by over 30%, and the subsequent QA performance by up to 3%. Further qualitative and quantitative analysis verifies our design choices and highlights the significance of situational awareness in 3D reasoning tasks.

To sum up, our paper has the following contributions: (1) We recognize the lack of situational awareness as a sig-

nificant oversight in existing research. To address this, we introduce SIG3D, a situation-grounded 3D VL reasoning architecture, specifically designed to fill this void. (2) We propose an anchor-based approach to situational estimation, which effectively narrows the extensive search space in 3D environments for precise grounding of 3D positions and orientations with textual descriptions. Additionally, we investigate situational alignment and visual re-encoding mechanisms to leverage situational awareness for enhanced QA performance. (3) Our model demonstrates superior performance on two challenging datasets, SQA3D and ScanQA, surpassing the state of the art in both situational estimation and QA metrics. Ablation studies highlight the importance of situation-guided encoding, revealing its beneficial impact on general QA tasks.

2. Related Work

Vision Language Models (VLMs). Early transformer-driven [59] textual and visual encoders [17, 31] have facilitated great progress in recent vision language learning. Text-image contrastive models [30, 54] propose to align the feature space of two modalities with large-scale pretraining, fueling numerous downstream tasks from generalized open-vocabulary visual perception [21, 34, 36] to text-to-image generation [56]. Concurrently, some work uses text and vision encoders on separate modalities followed by feature fusion [18, 33] for multi-modal reasoning tasks. Since the emergence of Large Language Models (LLMs) [7, 58, 69], VLMs have experienced huge improvement with the help of LLMs as building blocks for multi-modal learning architectures. Specifically, recent work directly projects visual embeddings into language-space tokens as input to LLM [23, 40, 47, 70], or use the latent bottleneck structure for cross-modal visual decoding [3, 26, 37, 38], or treat LLM layers as encoder blocks for various visual tasks [49].

In the domain of visual question-answering (VQA) [4, 73], recent work has pushed the frontier towards video understanding [14, 28, 29, 40, 62], knowledge-based understanding [20, 22, 23, 41, 46, 57, 63], and commonsense reasoning [68]. Despite the outstanding performance in 2D image interpretation, most existing methods lack the capability to generalize to 3D scenarios. In contrast, our work studies the representation of visual information and its fusion with language embeddings in the 3D domain by targeting on the 3D situation-guided visual language interpretation.

Grounding Language in 3D Space. Compared with 2D images, knowledge such as spatial relationships, interactive exploration, and topological analysis, which only exists in the 3D world provides additional challenges and opportunities to develop better language models with stronger commonsense reasoning capability grounded in the real-world 3D scenarios. In this direction, early work seeks

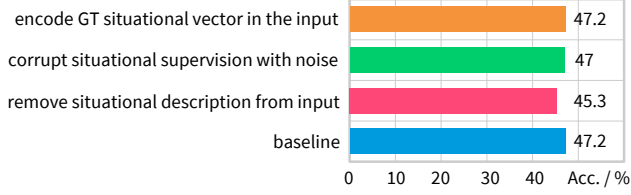


Figure 3. Results on variants of the representative SQA3D baseline method [44] demonstrate that situational understanding, despite being indispensable in perceiving the context of questions, makes negligible contribution in existing methods. This motivates a situation-guided 3D encoding mechanism in our model.

to ground isolated objects [1, 9] or objects within more complex scenes [2, 8, 19, 27] using natural language descriptions. Recently, with more collected 3D vision language datasets, several work starts to explore language-guided 3D visual interpretation and reasoning on a diverse set of datasets, including 3D scene captioning [10], open-vocabulary segmentation [16, 32, 51], and question-answering [5, 15, 25, 65, 74].

The success of LLMs also elicits the usage of them in 3D vision language reasoning for task decomposition [64], data generation, and multi-modal feature fusion [26]. Motivated by ScanQA [5], SQA3D [44] takes the first step into exploring the challenging 3D situational reasoning problem by developing a situated question-answering benchmark, and proposing the first joint learning baseline on the benchmark. Our work highlights the uniqueness and significance of situational awareness in the 3D vision language learning paradigm, leading to notably better 3D situational grounding and question-answering performance.

3. Pilot Study on Situated Reasoning

Despite pointing out the significance of situated understanding and reasoning, existing methods [44] fall short in providing effective situational estimation, as illustrated in Figure 2. This section delves into a pilot study examining the impact of situational understanding on downstream reasoning tasks. The SQA3D baseline [44] incorporates situational descriptions and uses ground truth (GT) situational vectors for supervision in a direct regression task. We investigate three variants of this baseline to assess the effect of situational understanding. In the first variant, we *remove the situational description and supervision* from the model, by passing in empty situational tokens. In another variant, we *corrupt the situation supervision* by introducing very large Gaussian noise to the GT vectors to effectively randomizing them. Finally, we try to *encode the GT situational vector in the input* with learnable multi-layer perceptron layers, which are then integrated with the visual and textual tokens.

Figure 3 demonstrates the results of this study, revealing negligible changes in performance across these variants. Notably, corrupting the GT situational information or di-

rectly incorporating it results in only marginal alterations in the QA outcomes. Omitting the situational description entirely from the input results in a mere 2% decline in accuracy. However, in the absence of this information, the model resorts to random guessing when determining the correct answer, as all responses depend on situational context. The findings from Figures 2 and 3 collectively indicate a deficiency in existing methods regarding situation vector estimation and the application of situational understanding in subsequent reasoning tasks. These unresolved challenges motivate the development of our proposed method.

4. Method

An overview of our approach SIG3D is illustrated in Figure 4. Our method begins with a set of points that represent a 3D scene, accompanied by a situational description and a question, which defines the overall context of the problem. We tokenize them into separate token embeddings (Section 4.1), and ground the textual description in the 3D scene with a vector comprising of location and orientation. We find direct single vector estimation to be challenging due to the vast and complex nature of the 3D search space, so we propose an anchor-based situational estimation strategy (Section 4.2). Subsequently, we re-encode the visual tokens from the perspective of situational vectors, enhancing the situational awareness for downstream reasoning tasks (Section 4.3). The finalized visual and textual tokens are fused by a transformer decoder to generate the final response.

4.1. Visual and Textual Tokenization

Leveraging input scene point clouds and textual prompts, our objective is to generate three distinct types of tokens: 3D visual tokens $z^{3D} \in \mathbb{R}^{N_v \times C_v}$, situational tokens $z^S \in \mathbb{R}^{N_s \times C_s}$, and question tokens $z^Q \in \mathbb{R}^{N_q \times C_q}$. Each type of token is characterized by two primary components: N , representing the number of tokens, and C , encapsulating the feature embeddings. To tokenize and capture the feature embeddings for situational and question inputs, we employ a shared text tokenizer E^{TXT} following prior methods [5, 44]. We assume that situational and question prompts are separated in the input data. If not, LLMs [7] can be used to parse the textual input without changing the semantic meaning of the sentences. However, there is a lack of consensus on a standard 3D visual tokenization method E^{3D} that is apt for the 3DVL reasoning task, prompting a more detailed exploration in the subsequent paragraphs.

Visual Tokenization. Given an input point cloud $\mathbf{p} \in \mathbb{R}^{N \times 3}$, most prior methods [5, 15, 44] adopt a VoteNet [53] detector to acquire object-level tokens $z^{3D} \in \mathbb{R}^{N_{\text{obj}} \times C_{\text{obj}}}$ as the visual representation, where N_{obj} is the number of object proposals, and C_{obj} is the object-level feature embeddings. However, we point out several problems with

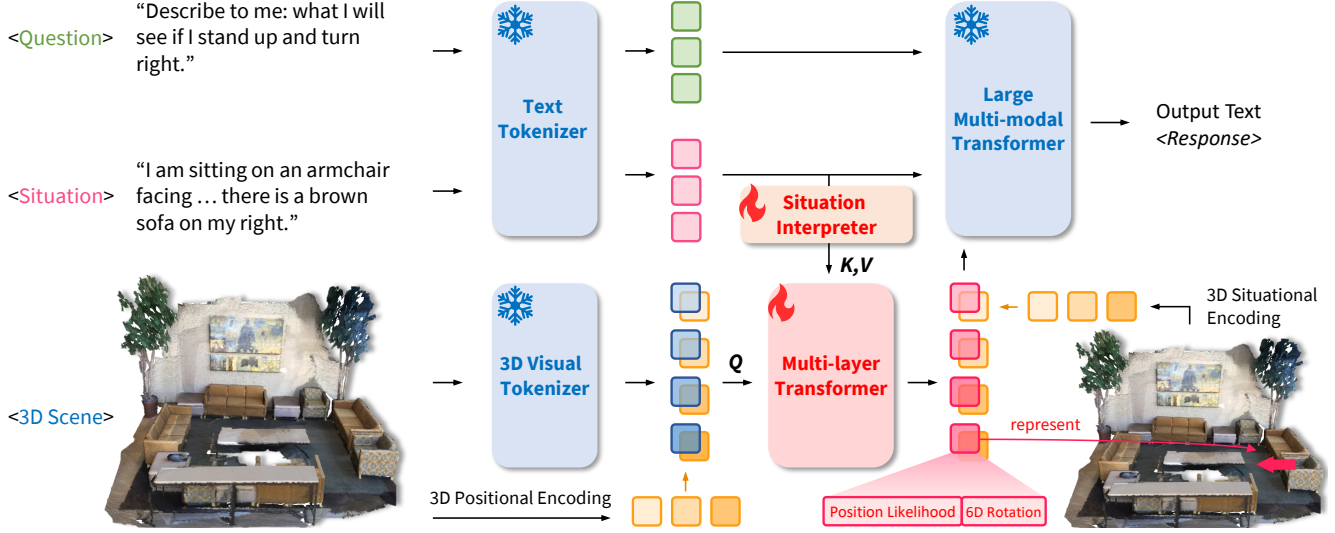


Figure 4. **Overview of our SIG3D model**, which includes 3D scene and text encoding, anchor-based situational estimation, situation-guided visual re-encoding, and multi-modal decoder modules. We tokenize the 3D scene into voxels, treat each token as an anchor point, and query the text tokens to predict a token-level position likelihood and rotation matrix to locate the situational vector associated with the text descriptions. Then we update the scene tokens with situational position encoding (PE), and finally perform the 3DVL reasoning task with a large transformer decoder.

this abstraction strategy: (1) A detection-based tokenization method tends to ignore the non-object regions in the scene, which can be indispensable in some reasoning scenarios (e.g., carpets on the ground, ceiling, walls.) (2) After object-level abstraction, the visual representation loses the high-level information of the scene (e.g., the shape of the living room, the corner of the kitchen.) (3) A supervised detector trained from scratch can only recognize objects within the training set (e.g., only 20 categories for ScanNet [13]), meaning that the method does not have zero-shot capability to reason about novel unseen objects that are inevitably common in real-world scenarios.

In light of this, we adopt a pretrained open-vocabulary voxel-based tokenization method from OpenScene [51]. The scene is first discretized into regular small 3D voxels and fed into a visual encoder for feature extraction:

$$x^{3D} = E^{3D}(\mathcal{V}(\mathbf{p})), \quad (1)$$

where \mathcal{V} represents the voxelization process, and E^{3D} is a Minkowski sparse 3D convolutional network [12]. The sparse network is pretrained by distillation from CLIP [54] embeddings of rendered multi-view 2D images, resulting in a feature map with better language alignment and 3D awareness. We take the upsampled bottleneck-layer feature embeddings from the encoder network, and compute the mean average over the z -axis (vertical) to project the voxels onto the x - y plane and treat the feature grids in the resulting 2D feature map as our N_v visual tokens. We find that this bird’s-eye-view projection results in a more compact representation and improves the final performance.

4.2. Situational Estimation

Given 3D visual tokens z^{3D} and situational tokens z^S , our objective is to estimate the situational vector \vec{s} referred by the situational description, which comprises of a position component s^{pos} represented by (x, y, z) coordinates, and a rotation component s^{rot} represented by (θ, ψ, ϕ) Euler angles, where pitch angles ψ are always defined as 0, meaning that situational vectors are defined to be parallel with the ground plane. The prior method [44] utilizes a transformer block to calculate the cross-attention feature between visual and language tokens, and directly regress a final situational vector out of the averaged attention map. We find such strategy producing very inaccurate estimation, as shown in Figure 2, due to the large search space in the entire 3D volume. Inspired by the recent 3D object detection methods [45, 66, 71], we reduce the search space by *turning the localization problem into a classification problem*.

Positional Embedding and Feature Fusion. After the voxelization and 3D encoding process, each 3D token associates with a 3D position (x, y, z) representing the center of its voxel. We first provide positional information to the model by generating learnable positional embeddings (PE) using a two-layer perceptron for each of the N_v visual tokens, and add learnable positional embeddings to the token features z^{3D} . We use a situation interpreter [55] to extract situational information, and ask the updated visual tokens to attend to these situational tokens with several transformer layers to produce the joint feature embeddings.

Anchor-based Situational Estimation. We treat each

output token of the feature fusion module as an anchor point, and use it to predict a position likelihood $p \in [0, 1]$ and a rotation estimation. Since each token has an associated 3D position (x, y, z) , the position likelihood p indicates how likely the situational vector locates at the center of this token (voxel). We define a soft ground truth for this classification task with a Gaussian kernel, meaning that the closer a token is to the actual situational vector s^{pos} , a higher ground truth probability p will be assigned to that token. In order to counteract the sparse supervisory signal and increase the positive supervision around the vector position, we adopt the peak enlarging technique in CenterPoint [66], where the size of the Gaussian kernel is increased (meaning that the σ is increased) to allow denser supervision around the vector position. Furthermore, we explore different rotation representation and find that compared with quaternion and $(\sin \theta, \cos \theta)$ representations, 6D vector proposed by [72] achieves the best performance. Hence, we adopt a situational estimation head with MLP layers to output 7-dimensional vector for each of the tokens, where the first channel represents the position likelihood and the other six channels represent the 6D rotation matrix. We take the center of the token with the peak position likelihood as our estimated s^{pos} , and convert its corresponding 6D rotation vector as our estimated s^{rot} . The estimation can be equivalently represented as a rotation matrix R and a translation matrix T . More discussion about the architecture and design choices is in Section 5.3.

4.3. Situation-guided Visual Encoding

After obtaining the situational estimation, we investigate a better approach to enhancing the downstream response generation, inspired by human cognitive processes. Intuitively, humans typically comprehend their immediate 3D environment by first interpreting their own situation in space, and then discerning their surroundings from an appropriate viewpoint. Our model is designed to emulate this natural strategy. Utilizing the situational vector \vec{s} , we adjust the coordinate system by repositioning the origin at s^{pos} , and reorienting the axes according to s^{rot} such that the new y -axis is aligned with the indicated direction. We keep the z -axis vertically oriented, and project the situational vectors onto the x - y plane. This is in line with the format of the dataset [44], where situational vectors are assumed to be parallel with the ground plane. Subsequently, we compute a new situation-guided PE for each of the N_v visual tokens, akin to the learnable 3D PE outlined in Section 4.2. They allow the model to grasp positional interrelations from the perspective of the current situation. These situational embeddings are added to the output embeddings of the situational estimation module, which consists of blocks featuring self-attention layers for visual tokens, succeeded by cross-attention layers that bridge visual

and situational information. This structure allows for the re-encoding of visual tokens under the influence of situational and question context, guiding the model to assign higher weights to situation-related and question-related visual tokens. The output, termed *situation-guided visual tokens*, embodies this re-contextualized understanding.

4.4. Question Answering Head

We follow existing methods [26] to use a large vision-language decoder to fuse the final visual and textual tokens and generate textual response to the input question. We explore both auto-regressive response generation, and classification-based answer prediction [5, 44]. For classification, we predict a vector $v^{\text{ans}} \in \mathbb{R}^{n_a}$ for the n_a answer candidates in the training set following [5].

5. Analysis in 3D VQA Task

We evaluate SIG3D for 3DVL reasoning on two challenging benchmarks, addressing both visually-oriented situational estimation and textually-focused QA tasks. We present a detailed examination of the implementation strategies adopted, the datasets employed, and the metrics applied in our research. For an exhaustive understanding, implementation and training details, and other additional information are available in the **supplementary materials**.

Datasets. We evaluate our method on SQA3D [44] and ScanQA [5], two challenging indoor 3D VQA datasets. Both datasets are derived from the ScanNet dataset [13], serving as the foundational source for their 3D scenes. SQA3D features over 33K question-answer pairs for the 3D VQA task and 26K unique situational descriptions for the situational estimation task. Each entry in this dataset includes a 3D scene point cloud, a situational description, a question, and pertinent annotations. ScanQA consists of over 41K question-answer pairs, without situational descriptions and situational annotations. We use it to demonstrate the generalizability of our method on general QA tasks. We use the splits provided by these datasets.

Evaluation Metrics. For SQA3D, in order to compare with baseline methods [44, 49, 74], we use a shallow transformer decoder task head to perform answer classification task, and evaluate the performance with exact matches (EM@1), which is equivalent to Top-1 answer accuracy. We also provide EM@1 on a breakdown of question types, including “What,” “Is,” “How,” “Can,” “Which,” and “Other,” based on the first word in the question sentence. Additionally, we evaluate situational estimation performance with localization accuracy and orientation accuracy. In both tasks, we use accuracy within different distance or angle thresholds as our metrics. For example, “Acc@0.5m” means accuracy of location estimation when positive threshold is set to 0.5 meter. For ScanQA,

Model	Question Breakdown						Overall
	What	Is	How	Can	Which	Other	
GPT-3 [7]	39.7	46.0	40.5	45.6	36.1	38.4	41.0
ClipBERT [35]	30.2	60.1	38.7	63.3	42.5	42.7	43.3
MCAN [67]	28.9	59.7	44.1	68.3	40.7	40.5	43.4
ScanQA [5]	28.6	65.0	47.3	66.3	43.9	42.9	45.3
SQA3D [44]	33.5	66.1	42.4	69.5	43.0	46.4	47.2
Multi-CLIP [15]	-	-	-	-	-	-	48.0
LM4Vision [49]	34.3	67.1	48.2	68.3	48.9	45.6	48.1
3D-LLM [26]	36.5	65.6	47.2	68.8	48.0	46.3	48.1
3D-VisTA [74]	34.8	63.3	45.4	69.8	47.2	48.1	48.5
SIG3D (Ours)	35.6	67.2	48.5	71.4	49.1	45.8	52.6

Table 1. Our proposed method SIG3D achieves state-of-the-art performance on SQA3D benchmark [44]. We perform the best on “Is”, “How”, and “Can” breakdown types of questions, as well as the average accuracy. The results are reported on test set.

Model	Localization		Orientation	
	Acc@0.5m	Acc@1.0m	Acc@15°	Acc@30°
Random	7.2	25.8	8.4	16.9
SQA3D [44]	9.5	29.6	8.7	16.5
SQA3D (<i>separate</i>)	10.3	31.4	17.1	22.8
3D-VisTA [74]	11.7	34.5	16.9	24.2
SIG3D (Ours)	27.4	59.1	28.7	42.5

Table 2. Our proposed method SIG3D performs significantly better than prior method [44] in situational estimation task. “Acc@0.5m” stands for localization accuracy with 0.5m threshold. “Acc@15°” represents orientation accuracy with 15° threshold. *separate* means disabling other tasks to let the model focus on situational estimation only.

Model	BLEU-1	BLEU-4	ROUGE	METEOR	CIDEr
BLIP2 [38]	29.7	5.9	26.6	11.3	45.7
Flamingo [3]	25.6	8.4	31.1	11.3	55.0
VN+MCAN [67]	28.0	6.2	29.8	11.4	54.7
SR+MCAN [67]	26.9	7.9	30.0	11.5	55.4
ScanQA [5]	30.2	10.1	33.3	13.1	64.9
3D-LLM [26]	39.3	12.0	35.7	14.5	69.4
SIG3D	39.5	12.4	35.9	13.4	68.8

Table 3. Performance of SIG3D on ScanQA dataset [5] is on-par with the state-of-the-art with large-scale text-3D pre-training. VN and SR stand for VoteNet and ScanRefer, respectively. 3D-LLM [74] leverages pretrained 2DVL foundation models and LLM models [3, 7, 37, 38], and is pretrained on a large-scale held-in 3D-text dataset before the finetuning on ScanQA.

we perform auto-regressive answer generation with large transformer decoder [26], and evaluate with BLEU [50], ROUGE [39], METEOR [6], and CIDEr [60] metrics.

5.1. Situated Question Answering

Baselines. Our study involves a comparative analysis with a range of representative baselines on the SQA3D dataset. In particular, we evaluate against **GPT-3** [7], **Clip-**

BERT [35], and **MCAN** [67], which are, as reported in prior work [44], baselines focused on language-only, 2D video, and 2D image QA, respectively. For GPT-3, we follow SQA3D [44] to convert the visual input into a caption using Scan2Cap [10] for LLMs to process. **ScanQA** [5] represents a 3D QA baseline that ignores the situational input. Both **SQA3D** [44] and **Multi-CLIP** [15] employ situational descriptions and annotations for direct regression tasks. **LM4Vision** [49] utilizes LLMs as visual and textual encoders. Additionally, **3D-VisTA** [74] undergoes a pretraining procedure on their large-scale 3D scene-text dataset, ScanScribe, prior to the finetuning on this dataset.

Situational Estimation. As shown in Table 2, our work performs significantly better than the state of the art [44, 74] in both localization and orientation estimation tasks. For 3D-VisTA [74], we use a pretrained model and finetune a new situation head with the SQA3D dataset following [44]. We also report a *random* baseline, in which we randomly sample position and orientation from a uniform distribution as a lower-bound performance. Note that original SQA3D performs only marginally better than the random baseline, meaning that it does not acquire any situational awareness, despite having the situational estimation loss. Disabling the QA task and asking the model to exclusively focus on the situational estimation task results in a slight better performance. Our method, with the anchor-based position likelihood estimation, results in a much better understanding of the 3D situational relationship. Our method also outperforms 3D-VisTA, which is pretrained on a large-scale 3D-text dataset, indicating that large pretraining alone is not enough to address the situational awareness problem. Note that we do not include the random baseline performance reported in [44], because each value is obtained by generating three random values and taking the *closest* one to the ground true, and thus it does not reflect a true “random” baseline.

Situated Question Answering. SIG3D outperforms prior

(a) Number of Visual Tokens				(b) Voxel size (in meters)			(c) Rotation representation		
	Acc@1.0m	Acc@30°	EM@1		Acc@1.0m	EM@1		Acc@30°	EM@1
128	48.9	38.2	49.2	0.01	54.1	49.5	Quaternion	31.4	50.0
256	59.1	42.5	50.9	0.02	59.1	50.9	6D vector	42.5	50.9
512	57.8	42.1	50.7	0.05	47.3	48.8	$\sin \theta, \cos \theta$	42.6	50.6

Table 4. Ablation study validates that our various design choices improves the performance. “Acc@1.0m”, “Acc@30°”, and “EM@1” are accuracy (%) for localization estimation, orientation estimation, and QA tasks. Our settings are marked in gray.

	Acc@1.0m	Acc@30°	EM@1
<i>3D Vision Encoders</i>			
Text-only (no vision input)	-	-	47.5
VoteNet [53]	37.4	28.2	49.1
3DETR [48]	47.2	29.1	49.4
OpenScene - OpenSeg [51]	57.5	41.6	50.2
OpenScene - LSeg [51]	59.1	42.5	50.9
<i>Language Tokenizer / Encoders</i>			
GloVe + LSTM [24, 52]	44.3	30.9	48.7
SBERT - MiniLM [55]	56.1	38.6	49.4
SBERT - MPNet [55]	55.9	40.6	49.7
SBERT - MPNet (finetune)	59.1	42.5	50.9

Table 5. Performance of SIG3D improves with stronger visual and language encoders. We find that open-vocabulary point encoder and MPNet-based sentence BERT leads to best performance. “Acc@1.0m” and “Acc@30°” stands for localization and orientation accuracy in situational estimation task. “EM@1” demonstrate exact match metric in QA task.

methods in most question breakdown categories and overall accuracy, as shown in Table 1. Our work achieves leading results *without large-scale pretraining* (compared with 3D-VisTA) and LLM (compared with GPT-3), indicating its superiority in situational awareness. Note that the LLM baseline GPT-3 achieves the best performance on the “What” category, suggesting the potential of stronger language encoder in interpreting the complicated question prompt.

5.2. General Question Answering on ScanQA

Baselines. We compare with 2D image VQA MCAN-based baselines [67], ScanQA [5], 3D-LLM [26] which leverages large-scale pretrained 2D VLMs and LLMs as backbone models, and 3D-VisTA [74] pretrained on their proposed large-scale 3D-text dataset.

Question Answering. As shown in Table 3, despite that the questions do not explicitly require situational understanding to answer in ScanQA, SIG3D achieves comparable results with state-of-the-art methods without the large-scale 3D-text pretraining and powerful 2D VLM and LLM backbone models. Our work pretrained on SQA3D [44] leads to higher performance on BLEU-1, BLEU-4, and ROUGE metrics, showing its generalizability on general 3D QA scenarios.

	Acc@1.0m	Acc@30°	EM@1
Baseline (joint optimization)	29.5	23.1	47.7
<i>How to achieve better situational estimation</i>			
+ 3D PE	38.8	23.6	47.8
+ 6D Representation	38.5	27.4	47.7
+ Anchor-based Estimation	58.8	41.9	48.2
<i>How to utilize situational estimation for better QA</i>			
+ 3D Situational PE	58.9	41.8	50.0
+ Visual Token Re-encoding	59.1	42.5	50.9
<i>Oracle Models (Ground Truth Situation Information)</i>			
Situation as direct input	100	100	47.7
Situation as intermediate input	100	100	53.9

Table 6. Ablation study verifies that our proposed modules leads to better situational estimation and better QA performance.

5.3. Ablation Study & Analysis

Vision & Language Encoders. We study the impacts of different visual and textual tokenizers in Table 5. It is observed that the open-vocabulary visual encoder (OpenScene) outperforms detection-based encoders (such as VoteNet and 3DETR) across all metrics. This superior performance of OpenScene is attributed to the limitations of 3D detectors, which are typically trained on a limited set of object categories, rendering them less effective in recognizing novel objects mentioned in textual prompts. Regarding language encoders, our findings indicate that a stronger backbone correlates with better performance, primarily due to its improved capability to interpret complex textual inputs. This leads to the suggestion of integrating LLM with our method to potentially further enhance performance, an avenue we intend to explore in future research.

Situated Awareness. In Table 6 we verify the crucial role of situational awareness in 3DVL task. Firstly, we show that 3D PE, 6D rotation estimation, and anchor-based position estimation all leads to much better position and orientation estimation performance. We further establish that situational PE and visual token re-encoding modules lead to better utilization of the predicted situational vector for QA task. Additionally, We design two oracle models under the assumption of having access to the ground truth situational vector as an input. The outcomes from these models reveal a critical insight: the model fails to effectively interpret situational information when it is directly incorporated into the input visual embeddings. This underlines the necessity








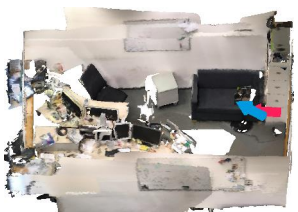
<p>Situational Description: After an exhausted day, I am lying on the bed closest to the window with my head on the pillows.</p> <p>Question: Can I see the television from my position on the bed?</p>  <p>Answer: No ❌</p>	<p>Situational Description: I am sitting in an armchair with a lamp behind me.</p> <p>Question: Which direction should I go if I want to open the window?</p>  <p>Answer: Right ❌</p>	<p>Situational Description: I am sitting on a chair in between a shelf on my right and a box on the other side.</p> <p>Question: Is the picture on the shelf or on the wall?</p>  <p>Answer: Wall ❌</p>	<p>Situational Description: I am leaning on the door facing the blinds.</p> <p>Question: I need to make a call so where can I find the phone?</p>  <p>Answer: Bed ❌</p>
<p>SIG3D (Ours)</p>  <p>Answer: Yes ✅</p>	 <p>Answer: Left ✅</p>	 <p>Answer: Shelf ✅</p>	 <p>Answer: Desk ✅</p>

Figure 5. Qualitative results demonstrate significant improvement of SIG3D over prior method. The first row is results from SQA3D [44], and the second row is results from our methods. In the 3D scene, **red**: Ground truth (GT) vector, and **blue**: Estimated vector.

of the intermediate representation and encoding mechanism we have proposed, affirming its importance in achieving optimal 3DVL task performance.

Architectural Design. We explore different architectural design choices of our model in Table 4. We find that the number of visual tokens sampled from the visual feature embeddings affects the performance of both situational estimation and QA tasks. Sampling fewer visual tokens increases the risk of missing the region of significance, while sampling more does not lead to a better performance as well. We study the size of voxels and find 0.02m to be the most effective choice, as OpenScene [51] backbone is pre-trained with the same voxel size. We also find $\sin \theta$, $\cos \theta$ and 6D vector representation performs a lot better than quaternion in rotation estimation task. This is consistent with the finding reported in [72].

5.4. Qualitative Analysis

Finally, we demonstrate some qualitative results of our SIG3D in Figure 5. We show the ground truth and estimated situational vectors in red and blue colors, respectively, in their corresponding 3D scenes. We also print the answers with red cross or green checkmark indicating the correctness. It is clear that our method performs significantly better in situational estimation task, resulting in vectors very close to the ground truth in both position and orientation perspectives. The better situational awareness

also aids the complicated embodied navigation and common sense QA activities. This also demonstrate great potential of our method in the development of indoor robotics and/or conversational agents.

Supplementary Material. The supplementary section offers an extensive analysis, encompassing a detailed examination of the *3D visual token activation changes* pre and post situational re-encoding. Additionally, it includes a comprehensive collection of *positive and negative samples*, an insightful *failure case analysis*, and a forward-looking discussion on *limitations and future work*.

6. Conclusion

In this paper, we introduce SIG3D, a situation-aware vision language model for 3D reasoning tasks. We propose to represent 3D scene as feature tokens, treat tokens as anchors points to estimate a situational vector from a text description, and use the estimated situation as guidance to align and re-encode the visual tokens to enhance the features for reasoning tasks. We observe consistent and significant performance gain on both situational estimation and question answering tasks.

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