

Sparse Multiview Open-Vocabulary 3D Detection

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Background

Conventional 3D detection methods often rely on predefined, closed sets of object categories, requiring expensive retraining and new annotations to adapt to new domains. Recent advances in vision-language models have enabled open-vocabulary detection in 2D., but applying these approaches to 3D detection typically requires dense 3D point clouds constructed from RGB-D sensors or extensive multi-view imagery. Existing methods are also constrained by the availability of high-quality 3D data, limiting their practicality in many real-world scenarios.

We propose a novel, training-free framework for open-vocabulary 3D object detection using sparse multi-view RGB images.

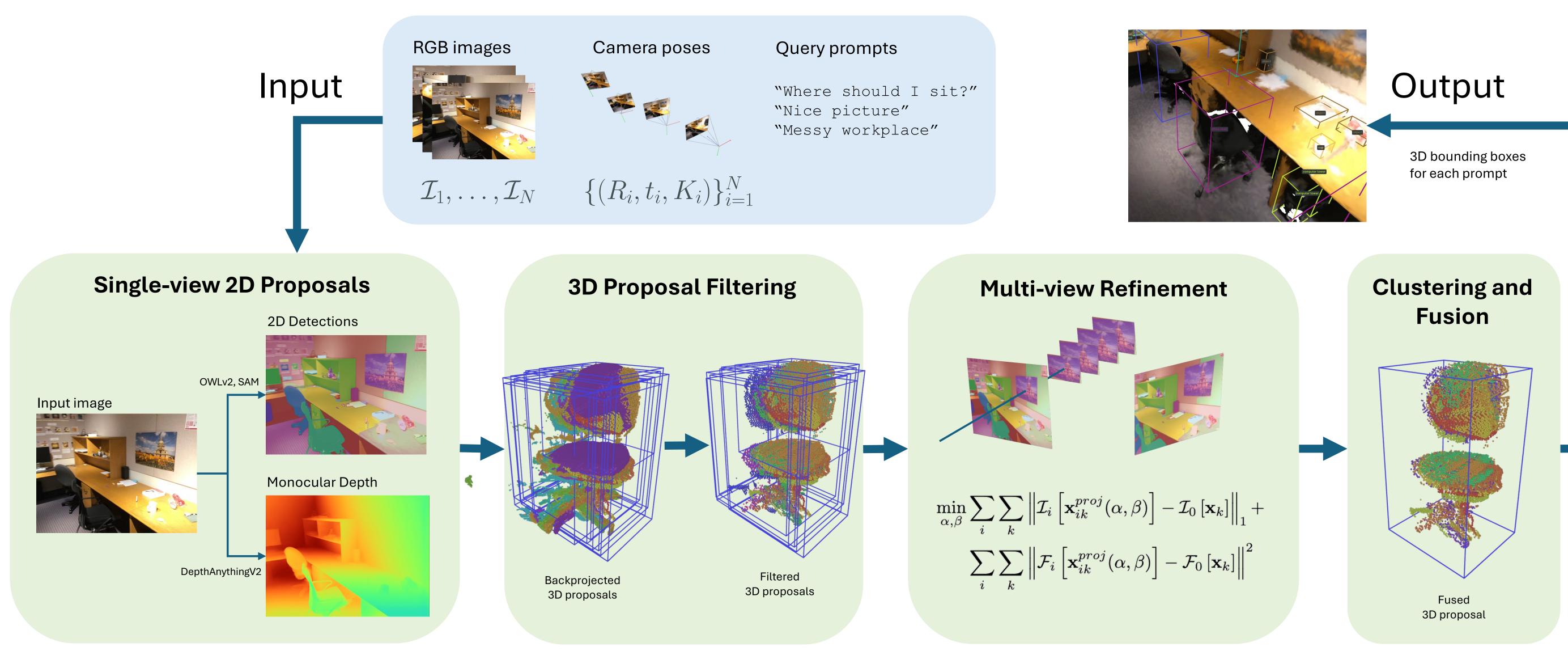
Contributions

 We introduce a novel, training-free framework for open-vocabulary 3D object detection using sparse multi-view RGB images.

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- We leverage pre-trained, off-the-shelf 2D networks for proposal generation and monocular depth estimation.
- We propose a three-step pipeline involving single-view proposal generation, multi-view refinement using feature consistency, and 3D bounding box fusion.
- Our method achieves competitive results without relying on 3D data and generalizes to unseen, long-tail vocabularies.

Approach



Overview of SMOV3D. Our method takes as input a sparse collection of posed RGB images together with a collection of text query prompts. The pipeline then conists of three steps. i) **Monocular 2D Proposals** For each prompt and image we perform 2D detection yielding a set of masks. These are then lifted to 3D using monocular depth. ii) **Multi-view Refinement** Lifted 3D point clouds are refined by optimizing a multi-view featuremetric loss that combines both photometric and CLIP consistency. iii) **3D Clustering and Fusion.** The optimized 3D point clouds are aggregated in 3D and greedily fused using a simple heuristic. The output is a collection of 3D bounding boxes. For visualization we show them overlayed on the ground-truth mesh.

Selected Results



Method	GT Depth	3D proposal	Mean	toilet	bed	chair	sofa	dresser	table	cabinet	bookshelf	pillow	sink
OV-3DETIC [2]	 Image: A second s	3DETR [†]	12.7	49.0	2.6	7.3	18.6	2.8	14.3	2.4	4.5	3.9	21.1
Object2Scene [4]	 Image: A set of the set of the	$L3DET^{\dagger}$	24.6	56.3	36.2	16.1	23.0	8.1	23.1	14.7	17.3	23.4	27.9
FM-OV3D [3]	 Image: A set of the set of the	3DETR^{\dagger}	21.5	55.0	38.8	19.2	41.9	23.8	3.5	0.4	6.0	17.4	8.8
OpenIns3D [1]	 Image: A set of the set of the	$Mask3D^{\dagger}$	43.7	79.5	70.5	76.9	15.8	0.0	53.1	40.1	41.2	7.1	53.1
SMOV3D (Ours) RGB-D	\checkmark	-	39.2	78.7	25.3	30.2	69.4	23.8	26.2	4.7	22.4	58.1	53.7
SMOV3D (Ours) Metric3Dv2 [†]	×	_	38.3	61.8	33.6	28.4	71.1	37.5	29.7	1.3	18.5	52.7	48.3

Figure 1:**Qualitative results on ScanNet.** Zero-shot 3D object detect detection, using the ScanNet10 categories as prompts.

Table 1:**Open-vocabulary Object Detection on ScanNet10.** We compare our method to point cloud-based methods. "[†]" denotes a component trained on ScanNet.

Method	Head	Common	Tail
Object2Scene [4]	_	10.1	3.4
OpenIns3D [1] with RGB-D	25.6	20.4	16.5
SMOV3D (Ours) RGB-D	21.0	27.6	23.2
SMOV3D (Ours) Metric3Dv2	18.4	18.6	22.6
SMOV3D (Ours) DepthAnythingv2	11.7	18.9	11.9

Table 2:**Open-vocabulary Object Detection on Scan-Net 200.** We present results (mAP_{25}) for the Head, Common and Tail category splits. Our method performs just as well on long-tail classes (Tail) as on the most frequent ones (Head).

References

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