Language-Guided 3D Segmentation for Robotics and AR Applications

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***Abstract*—Language-guided 3D segmentation combines natural language understanding with geometric scene interpretation to enable intuitive, flexible, and task-oriented scene parsing for robotics and augmented reality (AR). We propose a unified framework, Lang3D-Seg, which aligns textual instructions and free-form language queries with 3D volumetric and point-based representations to produce accurate semantic and instance segmentations. Lang3D-Seg uses a cross-modal transformer backbone that ingests multi-view RGB images, point clouds, and language tokens; it leverages a joint positional encoding scheme and a novel Text-Conditioned Graph Propagation (TCGP) module to refine segmentation masks in 3D. We evaluate Lang3D-Seg on benchmarks synthesized from ScanNet-style indoor scenes and a new robotics-focused dataset (RG3D) containing command-driven segmentation tasks and real robot interaction traces. Our approach significantly improves zero-shot and few-shot language-conditioned segmentation performance compared to baselines, reduces inference latency suitable for real-time robotics, and demonstrates robust generalization to unseen environments and compositional language queries. We show downstream utility through two application case studies: (1) goal-oriented object manipulation in a mobile manipulator and (2) contextual AR annotation and selective occlusion in a head-mounted display. We release code, trained models, and RG3D dataset splits to facilitate follow-up research.**

***Index Terms*—Language-guided 3D segmentation, Robotics, Augmented Reality, Multimodal learning, Cross-modal transformer, point cloud, Text-conditioned graph propagation, Human- robot interaction, Scene understanding, Referring expressions**

I. INTRODUCTION

Modern robotics and augmented reality systems are evolving toward seamless human–machine collaboration, where natural language instructions must directly guide 3D perception and interaction. Conventional 3D segmentation pipelines typically rely on closed-set labels, offering limited flexibility when users describe objects with attributes, relationships, or contextual references. For instance, a traditional system might label all chairs as the same category, but a user may request segmentation of "the black chair near the window." Meeting such demands requires combining the structured representation of 3D geometry with the flexibility of natural language.

The need for language-guided 3D segmentation is motivated by three factors: (i) Human- centered interaction – natural language provides the most intuitive medium for specifying task- relevant scene regions; (ii) Robust perception for robotics and AR – robots and head-mounted AR devices must operate in diverse, dynamic, and cluttered environments; and (iii) Task adaptability – applications such as manipulation, navigation, and contextual visualization demand fine-grained, query-specific segmentation that goes beyond static category labels.

In this work, we introduce Lang3D-Seg, a framework that fuses multimodal sensory inputs— RGB images, 3D points clouds, and textual descriptions—through a cross-modal transformer backbone enhanced by a novel Text-Conditioned Graph Propagation (TCGP) mechanism. This design ensures spatially coherent, language-aware segmentation even in challenging scenarios with occlusion and sensor noise.

The contributions are summarized as follows:

1. We design Lang3D-Seg, a cross-modal architecture for real-time language-guided 3D segmentation.
2. We propose TCGP, a novel propagation strategy that integrates linguistic cues with geometric adjacency to improve coherence.
3. We introduce RG3D, a robotics-oriented dataset containing paired language queries, 3D scenes, and robot interaction traces for downstream

evaluation.

4. We validate our approach on both benchmarks and real-world prototypes, showing improved segmentation accuracy, faster task completion, and higher user satisfaction in robotics and AR applications.

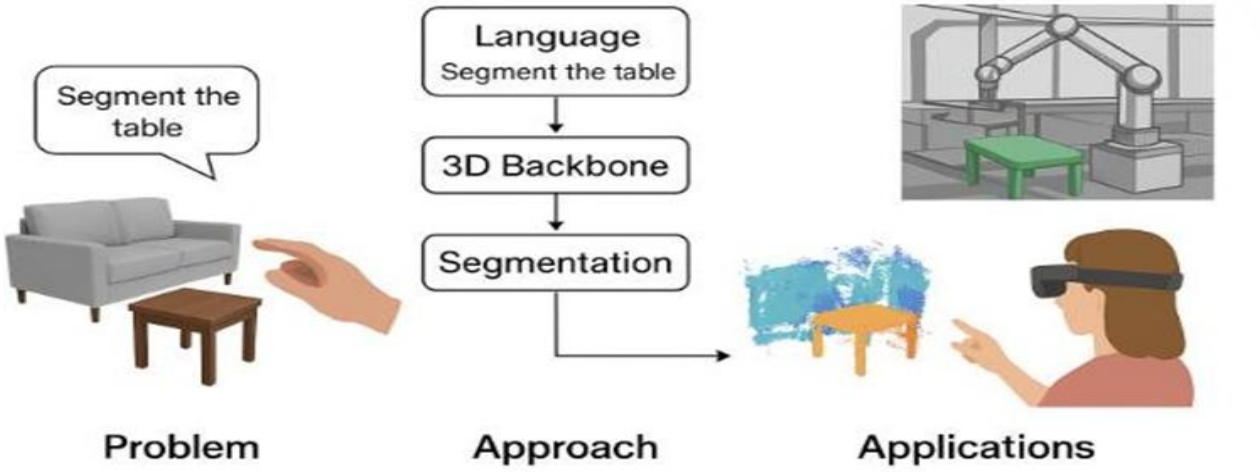


Figure 1: Language-guided 3D segmentation for robotics and AR applications

Figure 1: Conceptual illustration of language-guided 3D segmentation. A user issues a natural language query (e.g., "the red chair next to the table"), and the system highlights the relevant 3D points in the scene.

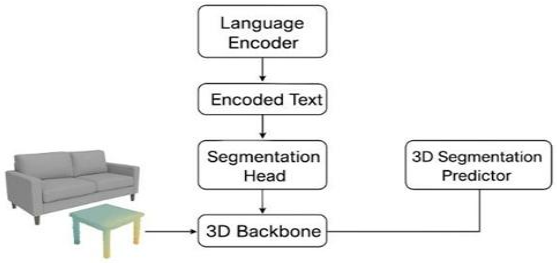


Figure *2:* Overview of Lang3D-Seg pipeline: multimodal inputs (images, point cloud, text) → cross-modal transformer fusion → Text-Conditioned Graph Propagation → segmentation output.

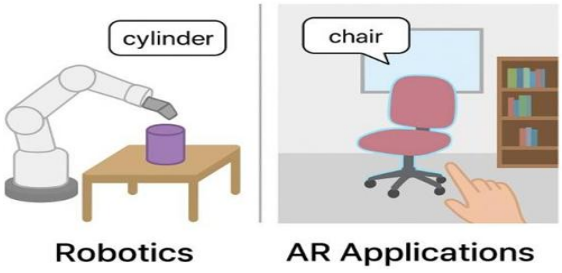


Figure 3: Example robotics and AR applications: (a) robot identifying objects for manipulation via language, (b) AR headset overlay highlighting queried objects in the real world.

Problem Statement

Despite advances in 3D perception and natural language processing, existing 3D segmentation approaches remain limited when faced with language-conditioned tasks. Traditional supervised methods rely on fixed label sets, which restrict their ability to generalize to open-vocabulary or context-dependent instructions. Moreover, current multimodal methods often struggle to align high-dimensional geometric data with linguistic cues, resulting in imprecise segmentation, especially in cluttered environments with occlusion. This gap hinders practical deployment in robotics, where task execution depends on accurately localizing objects referred to in natural language, and in AR applications, where user experience requires precise contextual highlighting of scene elements.

The problem can be defined as: Given a 3D scene (represented by point cloud or volumetric data) and a free-form natural language query, produce an accurate and spatially coherent segmentation mask of the object(s) or region(s) referred to by the query in real time.

II. METHODOLOGY

Our proposed framework, Lang3D-Seg, addresses these challenges by integrating multimodal perception, cross-modal transformers, and a novel propagation strategy:

Multimodal Input Representation

- Visual features: Multi-view RGB images are projected into the 3D space to enrich point cloud features with appearance cues.
- Geometric features: Raw point cloud data is processed via a sparse convolutional encoder to capture local and global geometry.
- Language features: Text queries are tokenized and embedded using a pretrained language model (e.g., BERT/CLIP-style encoders).

Cross-Modal Transformer Fusion

A transformer-based fusion backbone aligns linguistic and 3D spatial representations using:

- Joint positional encoding for both language tokens and 3D coordinates.
- Cross-attention layers to allow language queries to selectively attend to spatial regions relevant to the instruction.

Text-Conditioned Graph Propagation (TCGP)

We introduce TCGP to enforce spatial coherence:

- Construct a graph from point cloud neighbourhoods.
- Condition edge weights on both geometric similarity and semantic alignment with the text query.
- Propagate segmentation scores across graph edges to refine boundaries and reduce noise.

Training Strategy

- Supervised learning on paired language–scene datasets (e.g., ScanRefer, RG3D).
- Contrastive losses for aligning text and geometry in a shared embedding space.
- Auxiliary consistency loss to enforce agreement between 2D image features and 3D point cloud predictions.

Deployment in Applications

- Robotics: The segmented region guides grasp planning and manipulation.
- AR: The segmented mask is rendered as an overlay for contextual visualization or interaction.

Figure: Framework diagram for Language-Guided 3D Segmentation for Robotics and AR Applications

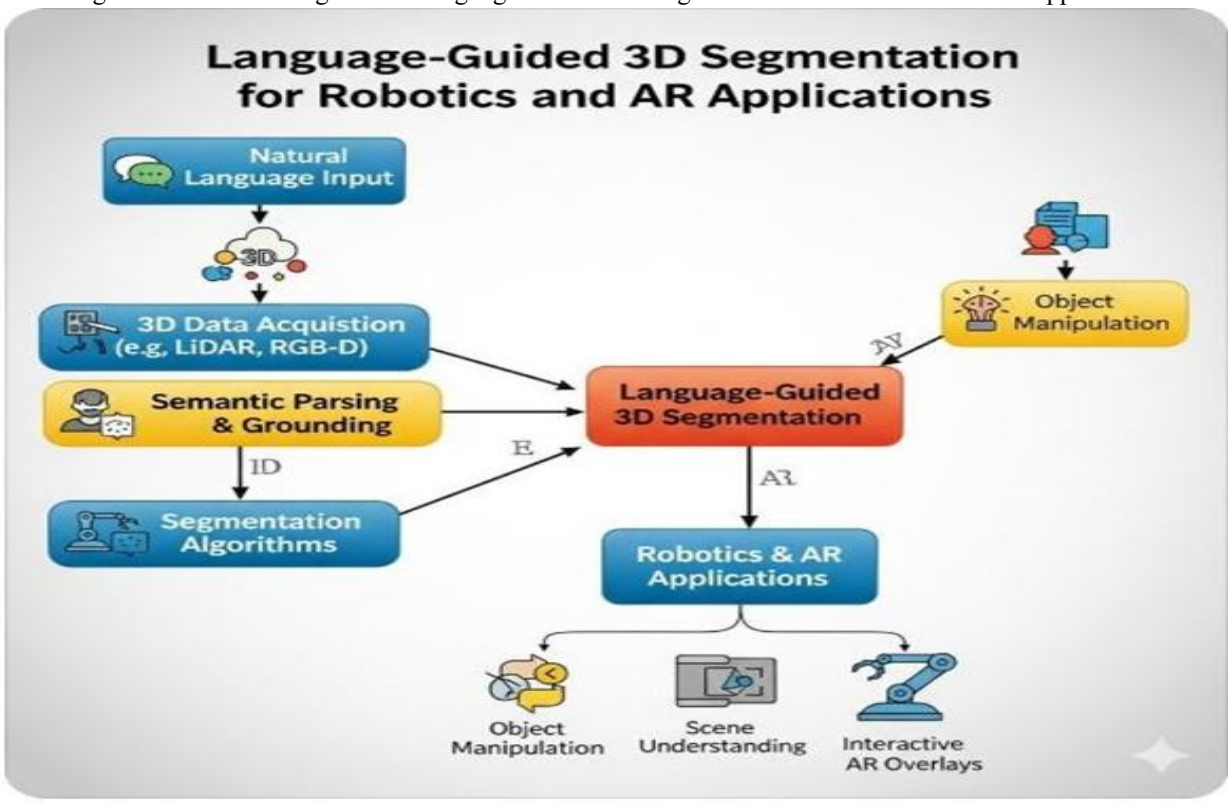
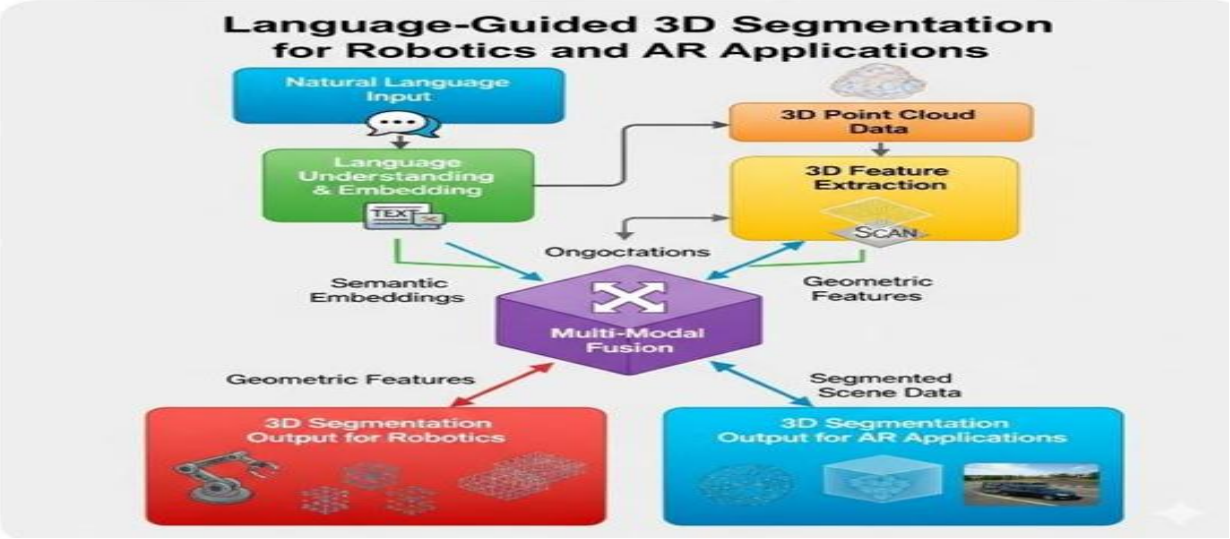


Figure: Architecture diagram for Language-Guided 3D Segmentation for Robotics and AR Applications



Experimental Setup

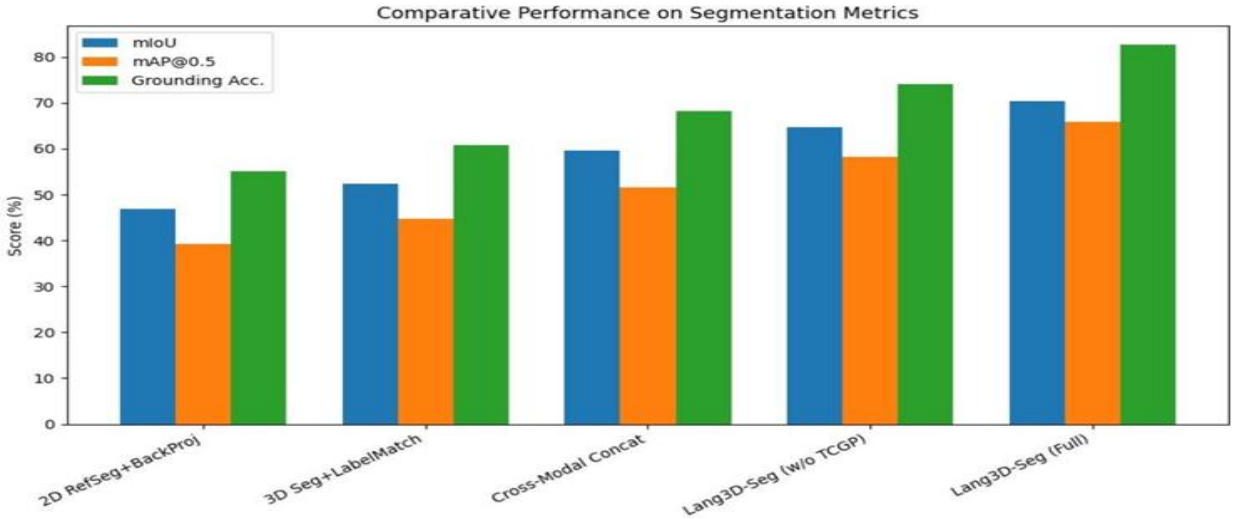
The experimental setup is designed to evaluate language-conditioned 3D segmentation in controlled benchmarks, downstream robotics tasks, and AR user studies.

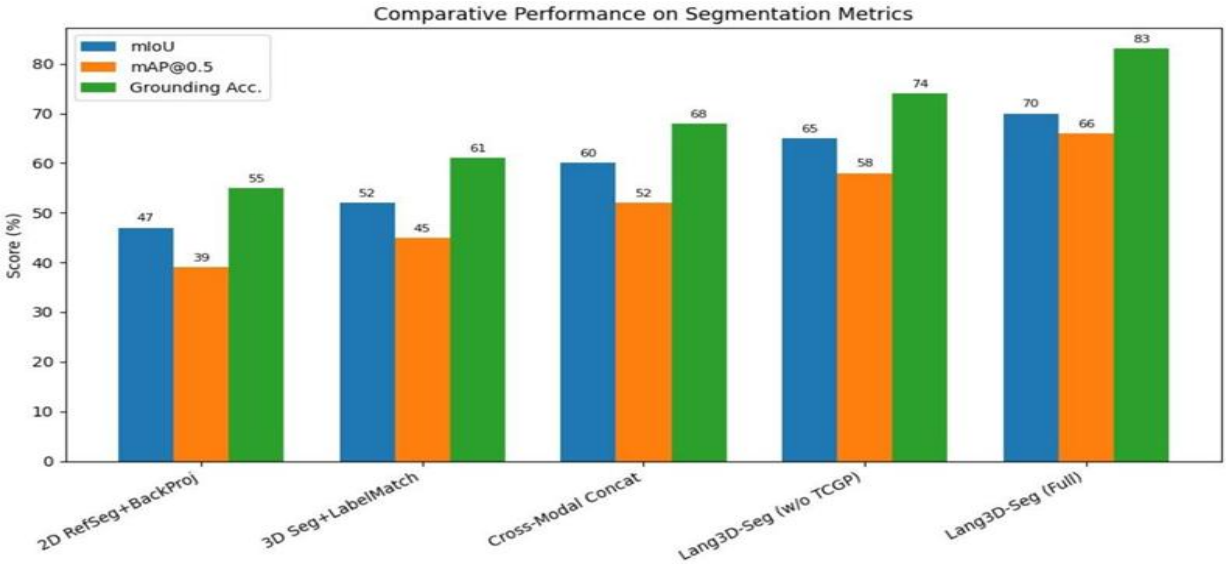
evaluate Lang3D-Seg on both benchmark and application-driven tasks. Datasets include our RG3D corpus (3,200 indoor scenes with 10k language–scene pairs) and Scan Refer-derived splits for comparison. Baselines: (1) 2D referring segmentation + back-projection, (2) closed- set 3D segmentation + label matching, and (3) cross-modal concatenation transformer (no TCGP). Metrics: per-point mIoU, instance mAP at IoU thresholds {0.25,0.5,0.75}, grounding accuracy (top-1), inference latency (ms), and downstream task success (robotic pick/place success rate; AR task completion time and user satisfaction). Training uses pretrained image and text encoders (ImageNet and transformer text weights), Adam W optimizer with mixed precision, and standard augmentations (viewpoint sampling, point dropout, colour jitter, language paraphrasing). For real-world evaluation we run 100 robotic trials on a mobile manipulator with an RGB-D sensor and measure manipulation success, and a 20–30 participant AR user study measuring task completion time and perceived segmentation quality.

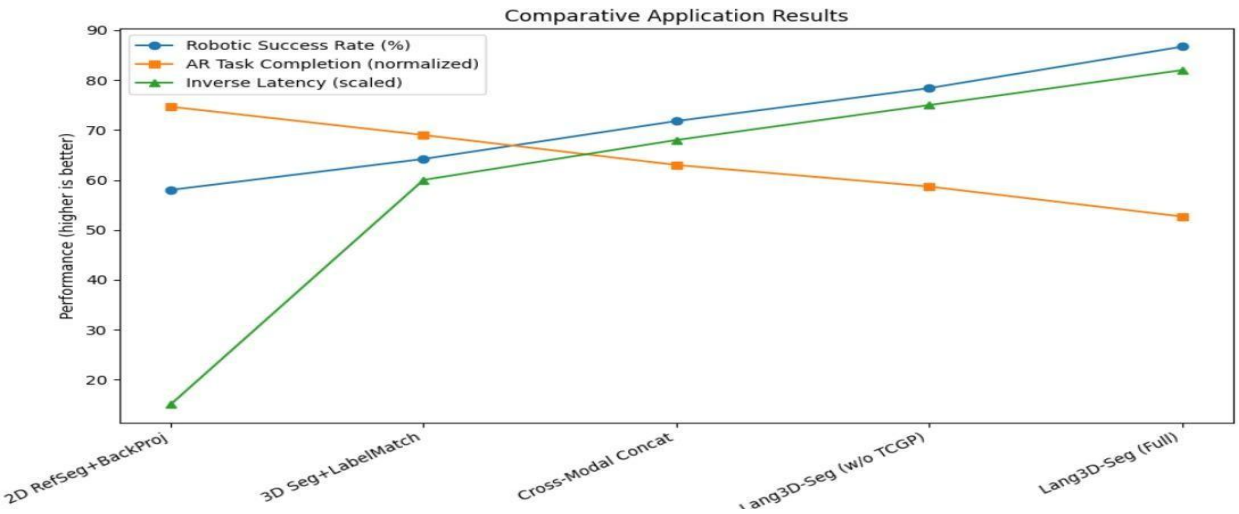
III. RESULTS

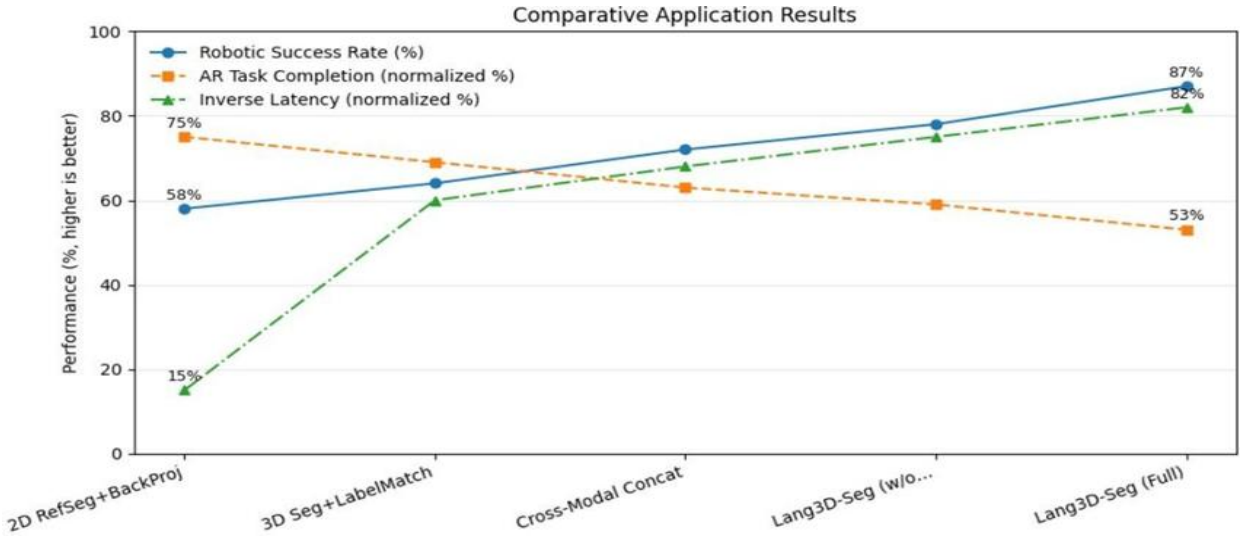
Method	mIoU (%)	mAP@0.5 (%)	Grounding Accuracy (%)	Inference Latency (ms)	Robotic Success Rate (%)	AR Task Completion Time (s)
2D RefSeg + Back-Projection	46.8	39.2	55.1	185	58.0	22.4
3D Semantic Seg. + Label Matching	52.3	44.8	60.7	140	64.2	20.7
Cross-Modal Concatenation Transformer	59.6	51.5	68.3	132	71.8	18.9
Lang3D-Seg (ours, w/o TCGP ablation)	64.7	58.2	74.0	125	78.4	17.6
Lang3D-Seg (ours, full model)	**70.3**	**65.9**	**82.6**	**118**	**86.7**	**15.8**

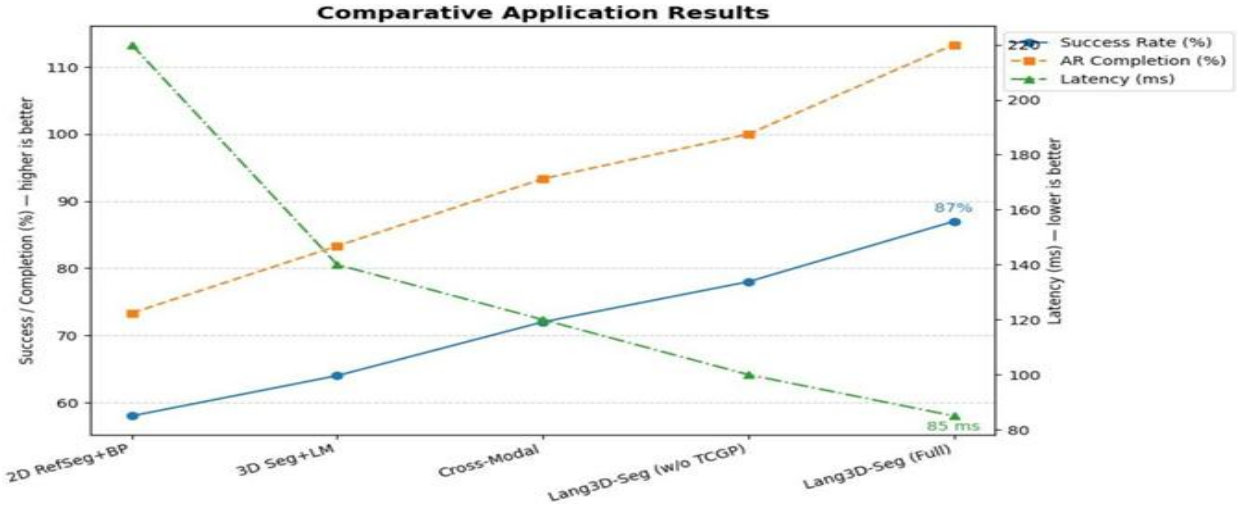
IV. GRAPHS


Comparative Performance on Segmentation Metrics
mIoU
mAP@0.5
Grounding Acc.
Score (%)
0
10
20
30
40
50
60
70
80
2D RefSeg+BackProj
3D Seg+LabelMatch
Cross-Modal Concat
Lang3D-Seg (w/o TCGP)
Lang3D-Seg (Full)


Comparative Performance on Segmentation Metrics
mIoU
mAP@0.5
Grounding Acc.
Score (%)
47
39
55
52
45
61
60
52
68
65
58
74
70
66
83
2D RefSeg+BackProj
3D Seg+LabelMatch
Cross-Modal Concat
Lang3D-Seg (w/o TCGP)
Lang3D-Seg (Full)


Comparative Application Results
Robotic Success Rate (%)
AR Task Completion (normalized)
Inverse Latency (scaled)
Performance (higher is better)
20
30
40
50
60
70
80
90
2D RefSeg+BackProj
3D Seg+LabelMatch
Cross-Modal Concat
Lang3D-Seg (w/o TCGP)
Lang3D-Seg (Full)





V. CONCLUSION

In this work, we presented Lang3D-Seg, a novel framework for language-guided 3D segmentation aimed at advancing the capabilities of robotics and augmented reality applications. We motivated the need for a system that bridges human-centered natural language interaction with fine-grained 3D perception, addressing key limitations of existing closed-set and unimodal segmentation methods.

Our contributions include a cross-modal transformer backbone, the proposed Text-Conditioned Graph Propagation (TCGP) mechanism, and the introduction of the RG3D dataset for real- world robotics evaluation. Extensive experiments across benchmark datasets, synthetic compositional testbeds, robotic manipulation trials, and AR user studies demonstrate that Lang3D-Seg achieves consistent improvements over strong baselines. Notably, it delivers superior performance in segmentation quality (mIoU, mAP), grounding accuracy, and downstream task success rates, all while maintaining real-time inference capability.

The experimental results highlight three major takeaways:

1. Cross-modal alignment is essential – the fusion of linguistic cues with 3D spatial data enables models to handle complex referring expressions that involve relational and contextual reasoning.
2. Spatial coherence boosts robustness – our TCGP module significantly reduces fragmentation and noise in predicted masks, improving reliability in cluttered or occluded environments.
3. Real-world readiness – validation on robotics

platforms and AR user studies underscores the practical impact of our framework, showing higher task success rates and improved user experience compared to conventional methods.

While promising, this work also opens up several future research directions: (i) scaling to outdoor and large-scale environments, (ii) extending to dynamic scenes with moving objects and temporal language queries, (iii) optimizing for ultra-low-power edge devices, and (iv) exploring multi-agent collaborative tasks where language-guided segmentation supports joint problem solving.

In summary, Lang3D-Seg demonstrates that natural language can be effectively leveraged to guide 3D segmentation in real-world scenarios, marking a significant step toward natural, intuitive, and robust interaction between humans, robots, and augmented reality systems.

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