Language-Grounded Understanding of 3D Shapes via Foundation Models

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Outline

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Why Localized 3D Understanding?

Goal: Understand 3D shapes at the **sub-shape level**

- Keypoint detection (e.g. wing tip, leg joint)
- Part segmentation (e.g. wing, tail, fuselage)
- Semantic labeling without manual annotation
- Language-driven queries ("show me the wing")

Traditional approach:

- Expensive per-category 3D annotations
- Category-specific models
- Poor generalization to new shapes

Key Challenge

How can we achieve **fine-grained 3D understanding** without 3D supervision?

Our Insight

Leverage **Multi-Modal LLMs** and **2D foundation models** to bridge the gap from 2D→3D.

Contributions at a Glance

ZeroKey (ICCV 2025)

- First zero-shot 3D keypoint detector
- No 3D annotations needed
- **79.43%** IoU@0.10 (3× baselines)

PatchAlign3D (arXiv 2025)

- SOTA zero-shot 3D part segmenter
- Single feed-forward pass (0.4s)
- **56.9%** mIoU on ShapeNetPart

Common thread: Language grounding + 2D foundation models → localized 3D understanding **without 3D supervision**

Background: Foundation Models We Build On

Vision-Language Models

- **CLIP / OpenCLIP:** Contrastive image-text pre-training; shared embedding space for images and text
- **SigLIP:** Sigmoid-based variant — per-pair contrastive loss (no softmax)
- **GPT-4o:** Multimodal LLM with image understanding and reasoning

Visual Feature Extractors

- **DINOv2:** Self-supervised ViT producing dense local features; excels at spatial correspondence
- **Molmo:** MLLM trained with **pixel-level point annotations**; can output precise (x, y) coordinates

Key insight: These 2D models encode rich geometric and semantic knowledge.
Our work **transfers** this knowledge to 3D without 3D-specific supervision.

Two Complementary Approaches

ZeroKey (ICCV 2025)

- **Task:** Zero-shot 3D keypoint detection
- **Key idea:** Exploit pixel-level MLLM annotations across multi-view renderings
- **Pipeline:** GPT-4o → Molmo → back-project → HDBSCAN
- **Result:** Competitive with supervised methods; **no 3D annotations needed**

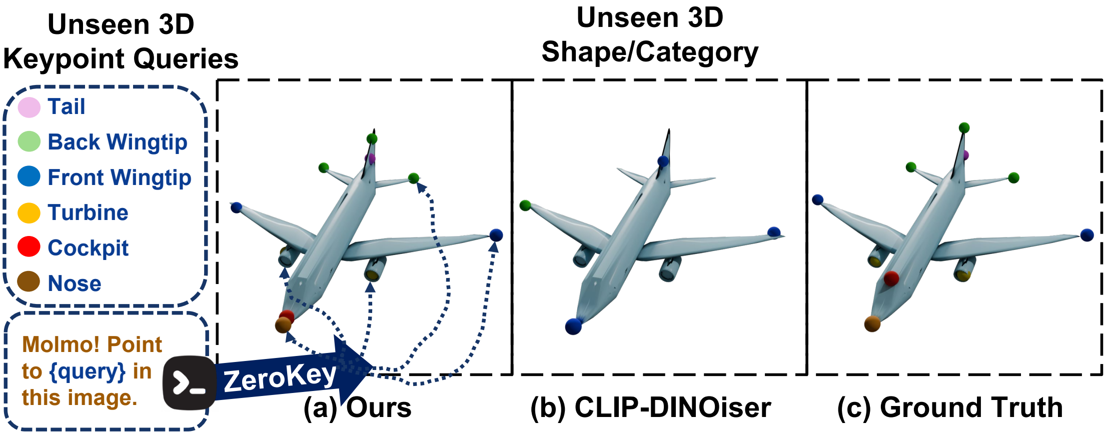
PatchAlign3D (arXiv 2025)

- **Task:** Zero-shot 3D part segmentation
- **Key idea:** Encoder-only 3D model with language-aligned patch features
- **Training:** DINOv2 distillation → SigLIP text alignment
- **Result:** SOTA across benchmarks; **single feed-forward pass**

Common theme: Foundation models + language grounding ⟶ localized 3D understanding

Outline

ZeroKey — Visual Overview



Without ground truth labels, ZeroKey leverages **pixel-level MLLM reasoning** to extract and name salient 3D keypoints — achieving competitive performance with supervised methods.

ZeroKey — Problem Setup

3D Keypoint Detection

- Given a 3D mesh, detect **semantically meaningful** points
- Schelling points: game-theoretic focal points people select independently
- E.g. wing tips, wheel centers, chair legs
- Traditionally requires dense per-point annotations

Zero-shot setting:

- No 3D keypoint labels at training time
- No category-specific fine-tuning
- Must *both* localize *and* name keypoints

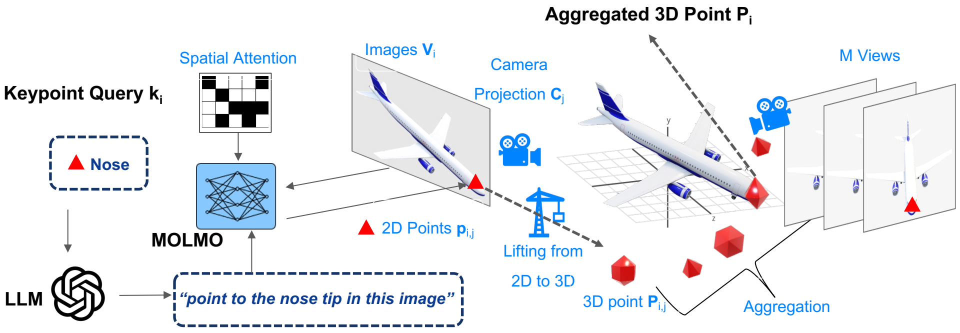
First-of-its-kind

ZeroKey is the first method to show that **pixel-level MLLM annotations** can be exploited for 3D keypoint detection *without any ground truth*.

Evaluation:

- KeypointNet benchmark
- Categories: airplane, chair, table
- Metric: IoU at geodesic distance thresholds

ZeroKey — Pipeline Overview



Stage 1: 2D Detection
Molmo localizes each named keypoint across N views

$$\mathbf{p}_{i,j} = \text{Molmo}(\mathbf{V}_j, k_i)$$

Stage 2: Soft Voting
Gaussian kernel weights for back-projection

$$\mathbf{w}_{i,j} \propto \sum \exp\left(-\frac{\|\mathbf{p}_{i,j}-\mathbf{p}\|^2}{2\sigma^2}\right)$$

Stage 3: Clustering
HDBSCAN aggregation with mutual reachability

$$d_{\text{mreach}}(a,b) = \max\{d_k(a),\ d_k(b),\ \|a-b\|\}$$

ZeroKey — Method: 2D Candidates

1. Text Candidate Generation (GPT-4o)

- **Input:** Rendered views of the shape
- **Prompt:** "List possible salient key points (in text)."
- **Output:** $\mathcal{K} = \{k_1, \ldots, k_N\}$ (e.g. "nose", "wing tip")
- Typically generates 6–10 keypoint names per shape

2. 2D Localization (Molmo)

- **Prompt:** `"Point to the {k_i} in this image."`
- **Output:** 2D coordinates $\mathbf{p}_{i,j}$ for each view $\mathbf{V}_j$
- Leverages Molmo's **point-level supervision** for precise localization
- Process across $M = 26$ views (default)

ZeroKey — Method: 3D Aggregation

3. Soft Voting Back-Projection

Stabilize ray casting with $h \times h$ patch refinement:

- Back-project patch $\mathbb{S}_{i,j}$ centered at 2D prediction $\mathbf{p}_{i,j}$
- Assign **Gaussian soft-voting weights** $\mathbf{W}_{i,j}$:

$$\mathbf{W}_{i,j} = \sum_{\mathbf{p} \in \mathbf{N}_{i,j}} \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{\|\mathbf{p}_{i,j} - \mathbf{p}\|^2}{2\sigma^2}\right)$$

- Higher weight for points closer to patch center
- Mitigates noise from sharp angular intersections
- $\sigma = h/3$ in implementation

4. Weighted HDBSCAN

Cluster 3D candidates $\mathcal{P}_i$:

$$d_{\text{mreach}}(a, b) = \max\{\text{core}_k(a), \text{core}_k(b), \|a - b\|\}$$

- Incorporate weights $\mathbf{W}_{i,j}$
- Filter outliers (Molmo noise)
- minPts $k = 10$ (fixed)
- **Output:** Centroid of densest cluster

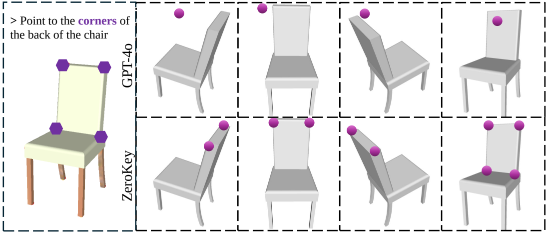
ZeroKey — Why Molmo?

Molmo is a recent MLLM trained with **pixel-level pointing data**:

- Can output precise (x, y) coordinates
- Understands natural-language spatial references
- Trained on human point annotations

Why not GPT-4o directly?

- GPT-4o reasons about images but outputs *bounding boxes*, not points
- IoU@0.10: GPT-4o $= 20.73\%$ vs. Molmo $=$ **79.43%**



(a) Ours Predicted Keypoint (b) Rendered Multiple Views

GPT-4o fails to precisely locate keypoints; Molmo succeeds due to pixel-level training.

Key insight: Point-level training is essential — scaling alone does not solve localization.

ZeroKey — Quantitative Results

KeypointNet benchmark (airplane, chair, table)

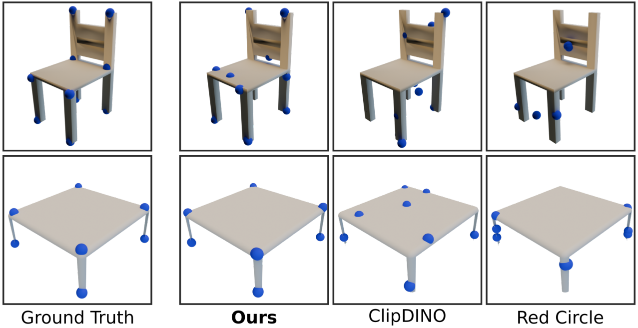
Method	**IoU (%) @ geo. dist.**		
	0.01	0.05	0.10
Supervised / Few-shot:			
UKPGAN (supervised)	6.54	26.55	46.49
FSKD (few-shot)	7.94	31.14	57.03
B2-3D (few-shot)	20.29	57.72	70.57
Zero-shot (ours):			
RedCircle	0.34	3.05	18.50
GPT-4o	0.48	6.04	20.73
CLIP-DINOiser	1.41	9.80	25.56
StablePoints	5.80	19.91	38.22
ZeroKey	**13.16**	**56.60**	**79.43**

Key Takeaways

- **79.43%** IoU@0.10 — **surpasses** supervised methods at larger thresholds
- **Zero-shot**: no 3D keypoint annotations
- **3**× improvement over CLIP-DINOiser

Note: Drop at small thresholds expected due to semantic (vs. geometric) focus.

ZeroKey — Comparison with Baselines



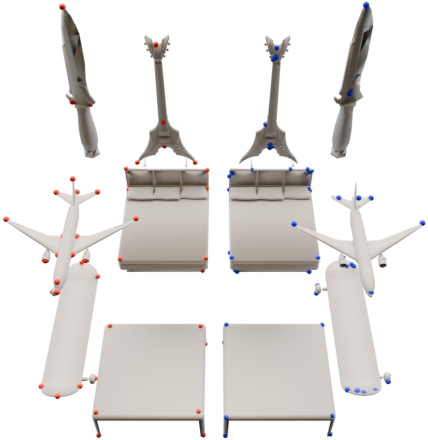
Visual Comparison:

- **CLIP-DINOiser:** Identifies prominent regions but fails to localize precisely
- **RedCircle:** Random sampling with CLIP similarity — noisy results
- **ZeroKey:** Precise localization according to text prompt

Key Difference

ZeroKey uses **point-specific prompts** + Molmo's pixel-level training for accurate localization.

ZeroKey — Qualitative Results

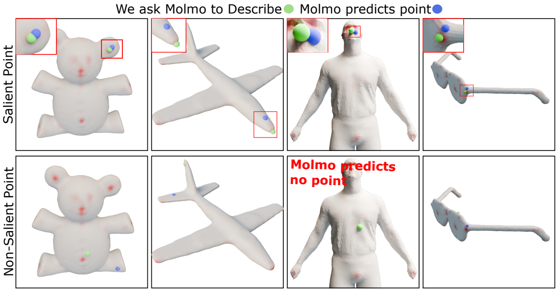


Observations:

- **Strong:** Distinctive, nameable parts (e.g., wing tips, wheel centers).
- **Weak:** Arbitrary surface points, symmetric duplicates.
- **Insight:** Detection quality correlates with how **nameable** a keypoint is.

ZeroKey — Analysis: Schelling Points & Describability

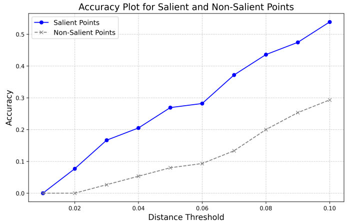
Schelling Points: Focal points people select independently due to prominence (game theory).



Ask Molmo to describe green point → use description to retrieve via ZeroKey (blue).

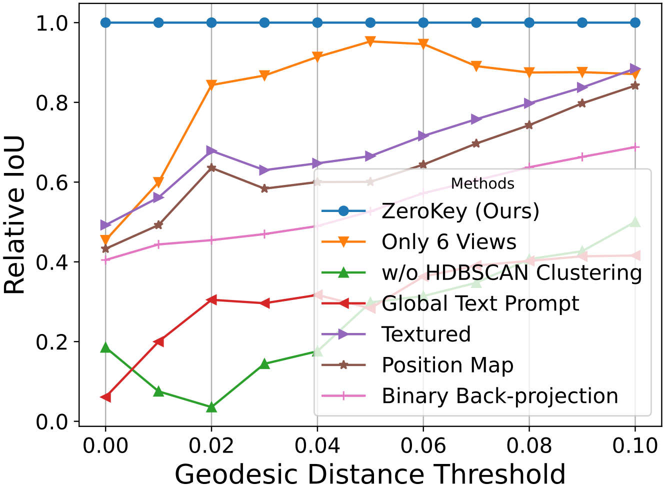
Key Findings:

- **Salient points** (semantically meaningful) are retrieved with much higher accuracy
- **Non-salient points:** ZeroKey may find similar parts or fail entirely
- Confirms: **describability** ≈ **detectability**



Salient vs. non-salient retrieval accuracy across distance thresholds.

ZeroKey — Ablation: Model Configurations



Impact of Modifications:

- **Original method** (blue)
- Global Text prompt (red)
- Alternative renderings (orange, purple, brown)
- No HDBSCAN (green)

This comparison shows the contribution of each component to overall performance.

ZeroKey — Ablation: Aggregation & Rendering

Multi-View Aggregation

6 views 26 views 46 views

- More views → more keypoints detected
- 6 views achieves **80%** of full performance
- Prompt: "corner of the table"

Key Findings

- **Clustering:** Direct averaging fails; **HDBSCAN is essential**
- **Soft Voting:** Gaussian weights outperform binary (weight=1)
- **Rendering:** Pointmap colors / mesh textures don't help (out-of-distribution for Molmo)

Robustness

Method works with **simple shaded renderings** — no special preprocessing required.

ZeroKey — Summary

Key Contributions:

1. **First zero-shot 3D keypoint detector** using MLLMs
2. Language grounding enables **both localization and naming**
3. **79.43%** IoU@0.10 — surpasses supervised at larger thresholds
4. Key ingredients: Molmo + HDBSCAN + multi-view aggregation

Limitations

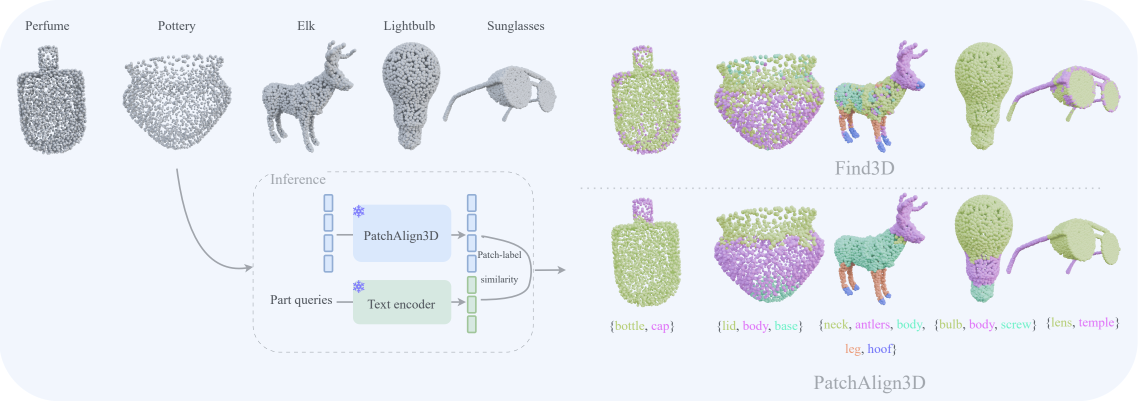
- **Fine-grained:** Lower accuracy at small distance thresholds (semantic vs. geometric focus)
- **Speed:** Requires multi-view rendering + MLLM inference per view
- **Symmetric parts:** May detect one instance of repeated keypoints

But what if we want dense part-level features instead of sparse keypoints?

$\Longrightarrow$ **PatchAlign3D**

Outline

PatchAlign3D — Visual Overview



An **encoder-only** 3D model producing language-aligned patch features — enabling zero-shot part segmentation in a **single feed-forward pass** without multi-view rendering at test time.

PatchAlign3D — Problem Setup

Zero-shot 3D Part Segmentation

- Given a point cloud + text queries (part names), segment the shape
- No test-time category-specific training
- Must generalize across diverse object types

Prior approaches (e.g. Find3D, COPS, SATR):

- Render multiple views at inference
- Run 2D foundation model per view
- Fuse predictions back to 3D
- Find3D: feed-forward but limited (**23.3%** mIoU)

→ **Slow** (>100s for SATR) and prompt-sensitive

PatchAlign3D Goal

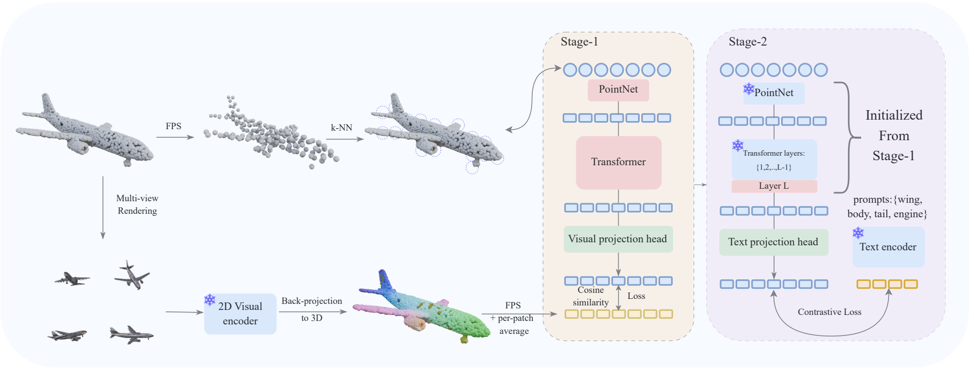
An **encoder-only** 3D model that:

- Operates in a **single feed-forward pass**
- Produces **language-aligned** patch features
- Achieves **SOTA** zero-shot part segmentation

Key Insight

Patch-level aggregation averages out annotation noise — more robust than point-level learning.

PatchAlign3D — Architecture



- **Input:** 2048 points (XYZ only)
- **Patches:** G=128 patches × 32 points
- **Encoder:** 12-layer transformer
- **Stage 1:** DINOv2 feature distillation
- **Stage 2:** Text-patch contrastive alignment
- **Inference:** $s_{i,j} = \frac{1}{\tau}\langle \mathbf{z}_i, \mathbf{t}_j \rangle + b$

PatchAlign3D — Loss Functions

Stage 1: Cosine-Similarity Regression

Align 3D patch features $\mathbf{f}_i$ with back-projected DINOv2 features $\mathbf{d}_i$:

$$\mathcal{L}_{2D} = \frac{1}{G}\sum_{i=1}^{G}\left(1 - \frac{\mathbf{f}_i \cdot \mathbf{d}_i}{\|\mathbf{f}_i\|\,\|\mathbf{d}_i\|}\right)$$

- $G = 128$ patches per shape
- DINOv2 features averaged across visible views
- Trains *all* transformer layers

Stage 2: SigLIP Contrastive Loss

Align patch features $\mathbf{z}_i$ with text embeddings $\mathbf{t}_j$:

$$\mathcal{L}_{\text{text}} = -\sum_{i,j}\left[y_{i,j}\log\sigma(s_{i,j}) + (1-y_{i,j})\log\sigma(-s_{i,j})\right]$$

- $s_{i,j} = \frac{1}{\tau}\langle \mathbf{z}_i, \mathbf{t}_j\rangle + b$ (learnable τ, b)
- **Fractional labels** $y_{i,j} \in [0, 1]$
- Freeze first 11 layers; train last block + proj. head

Why SigLIP over softmax? Sigmoid operates per-pair → naturally handles **multiple positive parts** per shape.

PatchAlign3D — Two-Stage Pre-Training

Stage 1: 2D→3D Feature Distillation

Teacher: DINOv2 (frozen)
Target: Transfer dense visual priors to 3D

1. Render N views of each shape
2. Extract dense DINOv2 features per view
3. Back-project to 3D: $\mathbf{d}(x) = \frac{1}{|V(x)|} \sum_r \mathbf{F}_r(u_r(x), v_r(x))$
4. Train with cosine-similarity regression

→ *3D patches capture local visual structure*

Stage 2: Contrastive Text Alignment

Freeze: Early 11 transformer layers
Train: Last block + projection head

1. Find3D annotations (>2M parts, 761 categories)
2. **SigLIP** contrastive loss
3. Fractional labels $y_{i,j} \in [0, 1]$ for soft matching
4. Handles noisy/overlapping annotations

→ *Patch features aligned with part-level text*

Why two stages? Joint training: 50.2% → Two-stage: **56.9%** mIoU

PatchAlign3D — Training Data

Based on Find3D data engine:

- **32,052** Objaverse shapes (28,827 train / 3,225 val)
- **761** object categories
- >**2 million** part annotations

Annotation pipeline (fully automatic):

1. 10 multi-view renderings per shape
2. SAM generates 2D part masks
3. Gemini 1.5 VLM assigns single-word part names
4. Back-project masks to point cloud

Key Advantage

- Same training data as Find3D
- But PatchAlign3D distills this into a **feed-forward encoder**
- No multi-view rendering at test time

Training details:

- 100 epochs per stage, batch size 32
- AdamW optimizer, lr 3×10^{-4}
- Input: XYZ coordinates only

PatchAlign3D — Main Results: ShapeNetPart

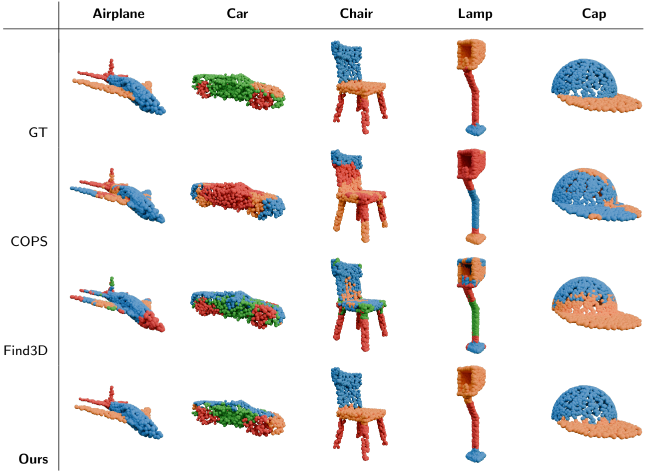
Zero-shot Part Segmentation on ShapeNetPart

Method	mIoU (%)	cIoU (%)	Type
PointCLIPv2	16.1	16.2	CLIP-based
SATR	32.8	36.3	Rendering (mesh)
Find3D	23.3	23.9	Feed-forward 3D
COPS	25.6	32.2	DINOv2 + multi-view
PatchAlign3D	**56.9**	**53.1**	**Feed-forward 3D**

+31.3% mIoU over COPS
+33.6% mIoU over Find3D

Consistent gains in **15 out of 16** categories
at **0.4s** inference (vs. 111s SATR)

PatchAlign3D — Qualitative Results: ShapeNetPart



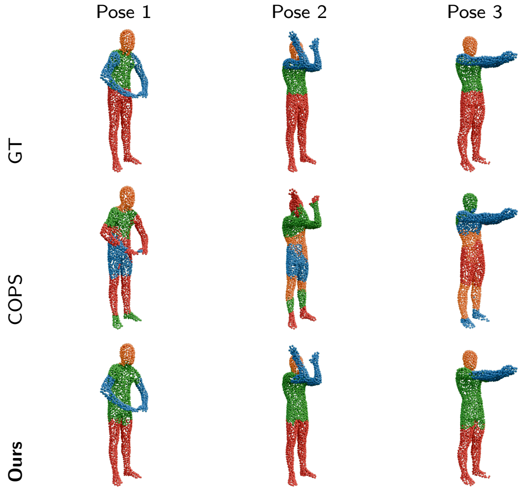
Zero-shot Segmentation

PatchAlign3D produces **sharper, more coherent** part boundaries.

- COPS: noisy, inconsistent
- Find3D: blurry boundaries
- **Ours**: clean parts

PatchAlign3D — Qualitative Results: FAUST Humans

Non-Rigid Human Body Segmentation



FAUST Results:

- **67.8%** mIoU (vs. 30.4% COPS)
- **+37.4%** improvement
- Parts: arm, head, leg, torso

Key Observation

PatchAlign3D remains **stable under pose variation**, while COPS degrades on non-rigid deformations.

PatchAlign3D — Results Across Benchmarks

	PatchAlign3D		Best Baseline	
Benchmark	mIoU	cIoU	mIoU	Method
ShapeNetPart	**56.9**	**53.1**	32.8	SATR
PartNetE	**41.4**	**42.2**	27.0	COPS
FAUST (humans)	**67.8**	—	30.4	COPS
ScanObjectNN	**22.7**	**25.3**	18.8	COPS
Objaverse (seen)	**37.5**	—	28.9	Find3D
Objaverse (unseen)	**35.6**	—	34.6	Find3D

Highlights

- **FAUST: 67.8%** mIoU on non-rigid human body segmentation (+37.4 over COPS)
- **ScanObjectNN:** Robust to **real-world noise** and partial scans
- **Unseen categories:** Strong generalization (35.6% vs. 34.6% Find3D)

PatchAlign3D — Inference Speed

Method	Time (s/shape)	Requires Multi-View?
SATR	111.0	Yes (mesh rendering)
COPS	1.38	Yes (DINOv2 per view)
Find3D	0.4	No
PatchAlign3D	**0.4**	**No**

Why is PatchAlign3D fast?

- Single feed-forward pass through 3D encoder
- No rendering pipeline at test time
- Text embeddings can be pre-computed

Practical Impact

- **$\sim$275$\times$ faster** than SATR
- Enables real-time / large-scale applications
- Point-cloud input (no mesh needed)

PatchAlign3D — Ablation Studies

Training Strategy (ShapeNetPart)

Strategy	mIoU
Stage 2 only	50.5
Joint training	50.2
Two-stage	**56.9 (+6.4)**

Text Encoder

Encoder	mIoU
SigLIP	46.4
Gemma-2-9B-it	54.8
OpenCLIP bigG	**56.9 (+2.1)**

2D Feature Encoder

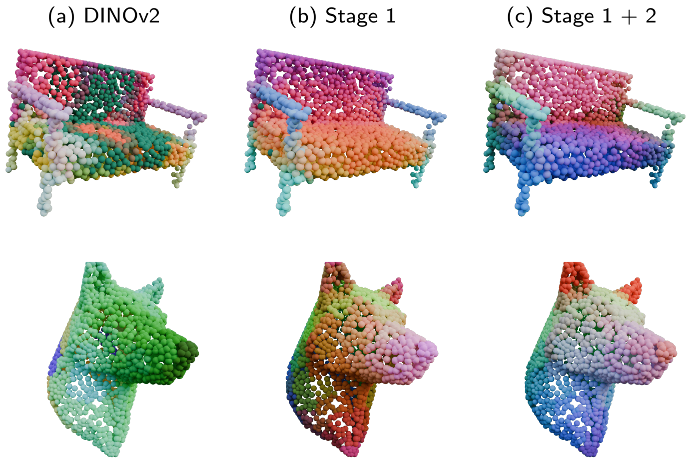
Encoder	mIoU
DINOv3	46.5
OpenCLIP bigG	49.3
DINOv1	51.8
DINOv2	**56.9 (+5.1)**

Freezing Strategy (Stage 2)

Strategy	mIoU
Full fine-tuning	49.4
Last 2 blocks	55.7
Last block	**56.9 (+1.2)**

Takeaways: Two-stage training essential • DINOv2 for vision, OpenCLIP for text • Fine-tune last block only

PatchAlign3D — Feature Evolution Across Stages



Features visualized via PCA to RGB.

Observations:

- **DINOv2:** Back-projected features are noisy, inconsistent
- **Stage 1:** Coherent, geometry-aware patterns emerge
- **Stage 2:** Preserves structure, adds text-driven semantics

Takeaway

Two-stage design is **essential**: Stage 1 refines, Stage 2 aligns.

PatchAlign3D — Keypoint Detection Extension

PatchAlign3D features also enable keypoint detection (connecting back to ZeroKey)

Method	**IoU (%) @ geo. dist.**		
	0.01	0.05	0.10
RedCircle	0.34	3.05	18.50
CLIP-DINOiser	1.41	9.80	25.56
ZeroKey	13.16	56.60	79.43
PatchAlign3D (zero-shot)	—	—	32.88
PatchAlign3D (few-shot)	—	—	**64.07**

Complementarity

PatchAlign3D's dense features + few-shot adaptation → **64.07%** IoU@0.10

Different Trade-offs

- ZeroKey: **truly zero-shot**, no training
- PatchAlign3D: requires pre-training but faster inference

PatchAlign3D — Summary & Limitations

Key Contributions

1. **First encoder-only** 3D model with language-aligned local features
2. **Two-stage pre-training:** DINOv2 distillation $\rightarrow$ SigLIP text alignment
3. **Multi-positive contrastive** with fractional labels handles noisy annotations
4. **56.9%** mIoU on ShapeNetPart (+31.3% over COPS)
5. **0.4s** inference — **275× faster** than SATR

Limitations

- **Data coverage:** Pre-trained on curated Objaverse subset (32K shapes of 800K+)
- **Fixed patching:** Not adaptive/hierarchical for varying point cloud sizes
- **Annotation quality:** Relies on SAM+VLM pseudo-labels (inherently noisy)

Future: Scale data, adaptive patching, inherit global 3D foundation model knowledge.

Outline

Limitations & Discussion

ZeroKey Limitations

- **Prompt quality dependency:** Poor keypoint names $\rightarrow$ poor detection
- **Non-salient points:** Fails on arbitrary or ambiguous locations
- **Inference cost:** Requires MLLM calls per view per keypoint
- **Symmetric objects:** Difficulty distinguishing left/right

PatchAlign3D Limitations

- **Patch resolution:** 128 patches may miss very small parts
- **Training data bias:** Performance tied to Objaverse coverage
- **Real-world gap:** 22.7% mIoU on ScanObjectNN
- **XYZ-only input:** Does not leverage color or normals

Both methods demonstrate the **viability** of foundation-model-based 3D understanding, while highlighting the **gap between synthetic and real-world** performance.

Conclusion

ZeroKey (ICCV 2025)
Sparse keypoints via MLLM
79.4% IoU, **flexible**

⟷ **Complementary** ⟷

PatchAlign3D
Dense features via distillation
56.9% mIoU, **0.4s**

Unifying Theme: Local 3D via Language

- 2D foundation models (MLLM, DINOv2) → 3D
- Language enables **localization + semantic naming**
- No 3D keypoint/part supervision needed

Open Challenges

- Real-world noise & occlusion
- Fine-grained / small parts
- Unified sparse + dense models

Future Directions

Short-Term

- Extend to articulated / deformable objects
- Finer patch resolution for small parts
- Integration with 3D scene understanding

Scaling Up

- Larger pre-training data (full Objaverse)
- Multi-granularity features (part $\rightarrow$ sub-part)
- Real-world point cloud inputs (LiDAR, depth)

Ongoing: RL from LLM Feedback

- LLM scores correspondence quality as reward
- Train DINO+LoRA via reinforcement learning
- Preliminary: **+20%** PCK on 2D matching
- **Next:** Extend to 3D keypoints

Vision

A single foundation model for 3D shapes at **any granularity**, language-grounded, no category-specific training.

Thank You!

Questions?

ZeroKey: `https://sites.google.com/view/zerokey`

PatchAlign3D: `https://souhail-hadgi.github.io/patchalign3dsite/`

Website: `https://s2.hk`

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