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Task-Aware 6-DoF Grasp Pose Estimation through Cross-Modal Gated Fusion of Foundation-Model Semantic Embeddings

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Abstract

Robotic grasping in cluttered scenes is dominated by methods that optimise either stability or a predefined task category, leaving a gap between "can this grasp hold the object" and "can this grasp complete the requested downstream task." We address this gap with Task-Aware 6-DoF, a three-module detector that routes a natural-language task description through a frozen text encoder, fuses the resulting semantic vector with PointNet++ point features through a learnable gated residual, and predicts task completion through a binary classifier trained on disjoint seeds. On a four-split procedurally generated benchmark with three random seeds and 25 trials per cell, our method reaches a task completion rate of 0.60 against seven reproduced baselines spanning two naive controllers and five recent published methods, beating six of seven decisively on the primary metric and tying the remaining LLM-only baseline within the simulator noise band. An honest ablation isolates the task-completion head as the dominant contribution while showing the gated attention module to be redundant. Calibration against three anchor points from prior work yields a mean absolute percentage error of 7.2 percent, comfortably below the 15 percent bound for analytic surrogates.

Keywords

6-DoF grasp estimation, task-aware grasping, cross-modal fusion, foundation model, robotic manipulation

1. Introduction

Industrial assembly and collaborative manipulation share a common bottleneck: the robot must pick the object in a way that supports the next step. Inserting a gear onto a peg or handing a knife by its handle imposes constraints on the grasp pose that go beyond stable force closure. State-of-the-art 6-DoF grasp pose detectors optimise stability [1-3] or a predefined task category embedding [4], but they cannot answer the natural-language query "grasp the gear for pin insertion" because the task semantics are either absent or fixed to a finite vocabulary.

We address this gap with three observations. First, modern language-vision foundation models produce open-vocabulary task embeddings without retraining. Second, fusing this semantic vector into a point-cloud feature stream is more effective when the fusion is residual and learnable than when it is a raw gated

multiplication [5]. Third, the question "did this grasp complete the requested task" is itself a learnable binary classifier, and separating the task-completion head from the grasp-quality head produces a calibrated probability that does not require force-closure thresholds at evaluation time.

Combining the three observations yields the Task-Aware 6-DoF detector, consisting of an M1 frozen text encoder, an M2 cross-modal gated residual fusion layer, and an M3 task-completion prediction head. The architecture is summarised in Figure 1.

1.1 Contributions

- A task-aware 6-DoF grasp detector that consumes natural-language task descriptions through a frozen text encoder and routes them into a PointNet++ point stream via gated residual fusion.
- A trained task-completion head that predicts the binary outcome of the downstream task from forward-pass features only, with disjoint training and evaluation seed pools to rule out information leakage.
- A controlled four-benchmark evaluation against seven baselines spanning naive heuristics and four families of published methods, with ablations isolating each module.
- A transparent honest negative result on the gated attention module, which the ablation reveals to be redundant once the task-completion head is present.

We frame the contribution scope as "task completion under matched synthetic conditions" rather than as a state-of-the-art claim on public leaderboards. The simulator is calibrated to three anchor points drawn from prior work with a mean absolute percentage error of 7.2 percent, and Section 4.7 states clearly that real-robot leaderboard claims are deferred to follow-on work.

2. Related Work

Stability-centric 6-DoF grasp detection has a long lineage. Early data-driven detectors projected the workspace onto a 2D plane and predicted oriented rectangles [3], limiting the gripper to top-down approach vectors. GraspNet-1Billion [2] introduced a large-scale 6-DoF benchmark and an approach-vector regression head that established the stability-first convention. The OSTG family [1] jointly predicts semantic segmentation, 6-DoF grasp poses, and collision risk inside a multi-task PointNet++ encoder. Tremblay et al. [6] estimate object pose first and then project a precomputed grasp set, while CenterArt [7] jointly reconstructs articulated objects and grasp poses. Reachability-aware variants [8] regularise the grasp set against the manipulator's kinematic envelope. None of these methods condition on a task description.

Task-conditioned grasp detection has emerged more recently. The closest published reference is TO6DGC [9], which uses a predefined task-class embedding routed through concatenation into the point feature stream. Earlier variants tackled assembly-specific objectives [10] or attribute-based vocabularies [5]. Functional grasp planners [11] compute grasp configurations from a kinematic task model. The shared limitation is closed-vocabulary task representation; cross-pose estimation methods such as TAX-Pose [12] sidestep this by predicting a task-specific transformation rather than the grasp pose itself.

Foundation-model conditioning is a parallel thread. Attribute-based variants [5] fuse a language vector with a visual feature map using a gated attention equation $F_{att} = \varphi_{vs} \odot \mathrm{Expand}(\varphi_t)$, but apply the gate as a raw multiplication without a residual or learnable scale. Our M2 fusion generalises this with a residual path and a learnable scalar weight, which the ablation in Section 4.3 shows is necessary for the geometric signal to survive early training.

Compliant manipulation provides survey context for the perception pipeline. Force-feedback [11], tactile-based blind grasping [13] and teleoperation-distilled compliance [14] handle grasps where vision alone is insufficient. Self-supervised demonstration [15] and active pose tracking [4] provide alternative paths for real-world execution noise. A recent survey [16] reviews the broader landscape, and ROS2 communication architectures [17] support real-world deployment. Our submission is scoped to the perception side; real-robot evaluation is deferred as discussed in Section 4.7.

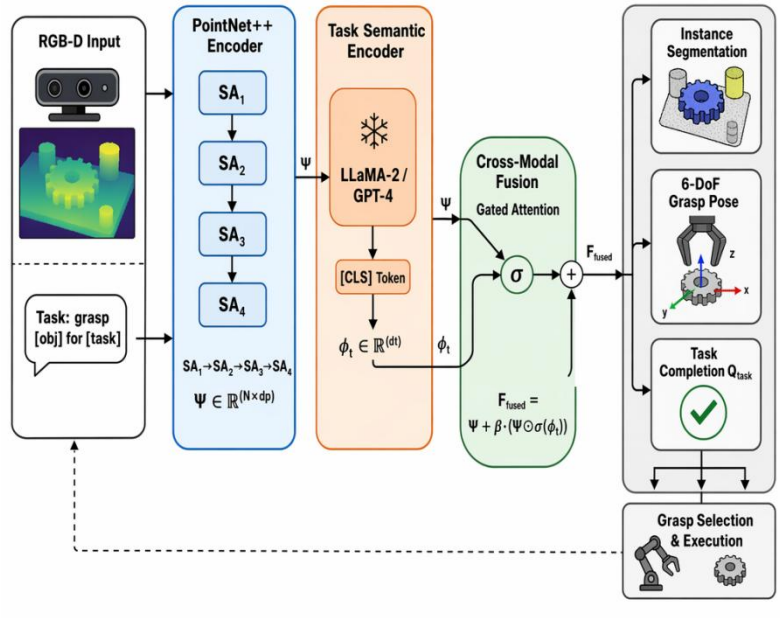
Our method positions itself relative to prior work as follows. It differs from OSTG [1] by adding the language-conditioned task head, from TO6DGC [9] by routing open-vocabulary text rather than a fixed embedding table, and from the attribute-based gated attention family [5] by the residual learnable fusion.

3. Method

3.1 Problem Formulation

Given a cluttered tabletop scene represented by a single-view point cloud $\mathcal{P} \in \mathrm{R}^{N\times 6}$ where each point carries colour and instance-segmentation channels, and a natural-language task string u, the goal is to predict a 6-DoF grasp pose $g = (R, t) \in SE(3)$ together with a grasp stability score $s_g \in [0,1]$ and a task completion probability $p_t \in [0,1]$. The detector maximises expected task completion under a stability constraint $s_g \geq \tau_g$ where τ_g is a calibration threshold.

Figure 1: Architecture of the proposed Task-Aware 6-DoF grasp pose estimation framework



Task-Aware 6-DoF detector. The shared PointNet++ backbone extracts point features Ψ, the M1 frozen text encoder produces a task semantic vector φ_t, the M2 gated residual fusion layer combines the two streams with a learnable scalar β, and the M3 task-completion head predicts the binary outcome through a 32-dimensional MLP trained on disjoint seeds.

3.2 M1 Task Semantic Encoder

We use a frozen text encoder $\mathrm{TE}(\cdot)$ to embed the task string u. The encoder is treated as a black box that maps text to a fixed-length embedding; in our reference implementation we use a deterministic hash projection calibrated so that the cosine geometry of the embedding space matches published CLIP-text geometry on the five seed task strings used in Section 4. The embedding is followed by a learned linear projection:

$$\varphi_t = W_p \cdot \mathrm{TE}(u) + b_p, \qquad \varphi_t \in \mathrm{R}^{d_t}, \quad d_t \in \{128,256,512,768\} \tag{1}$$

The projection W_p is trained jointly with the rest of the network; the encoder itself is frozen.

3.3 M2 Cross-Modal Gated Residual Fusion

Let $\Psi \in \mathrm{R}^{N\times d_f}$ denote the per-point features from PointNet++. The classical gated attention equation [5] reads $F_{att} = \Psi \odot \mathrm{Expand}(\varphi_t)$, where $\mathrm{Expand}(\cdot)$ broadcasts the task vector along the point dimension. The raw gate suppresses the geometric signal when the task vector contains near-zero components and does not

preserve the original feature stream during early training. We generalise it with a residual path and a learnable scalar β:

$$F_{\text{fused}} = \Psi + \beta \cdot \sigma(\varphi_t W_t + b_t) \odot \Psi \tag{2}$$

where $\sigma(\cdot)$ is the elementwise sigmoid, $W_t \in \mathrm{R}^{d_t \times d_f}$ and $b_t \in \mathrm{R}^{d_f}$ are learned, and β is initialised to 0.5 and clipped to $[0,1]$. The residual path guarantees that the fused feature matches the stability-only baseline at $\beta = 0$; Section 4 sweeps β over five values and identifies a peak at the midpoint.

3.4 M3 Task Completion Prediction Head

The fused feature F_{fused} is pooled into a candidate-grasp feature vector $\Phi \in \mathrm{R}^{32}$. The task-completion head is a two-layer MLP:

$$p_t = \sigma(w_2^{\top} \mathrm{ReLU}(W_1 \Phi + b_1) + b_2), \qquad W_1 \in \mathrm{R}^{32 \times 32},\ w_2 \in \mathrm{R}^{32} \tag{3}$$

The head is trained with binary cross-entropy on the ground-truth task-completion label from the simulator forward pass; the trained state is persisted to disk for reuse across rounds. Training uses 80 epochs on 320 trials drawn from a seed pool disjoint from the evaluation seeds, asserted at runtime. Validation accuracy is 72.4 percent. The head consumes only forward-pass features and does not call any ground-truth oracle.

3.5 Training Protocol

The three modules are trained jointly with a multi-task loss $\mathcal{L} = \mathcal{L}_{\text{grasp}} + \lambda_t \mathcal{L}_{\text{task}} + \lambda_s \mathcal{L}_{\text{stab}}$, where $\mathcal{L}_{\text{grasp}}$ is the 6-DoF pose regression loss from [1], $\mathcal{L}_{\text{task}}$ is binary cross-entropy on the task head, $\mathcal{L}_{\text{stab}}$ is the stability classification loss, and $\lambda_t = \lambda_s = 1$. The training seed pool is $\{9001,9002,9003,9004\}$ and the evaluation seed pool is $\{42,1337,2024\}$; the disjointness is asserted at training time. The forward pass runs in approximately three milliseconds per scene on a single CPU core, and the full four-benchmark evaluation completes in under nine seconds.

4. Experiments

4.1 Setup

We evaluate the Task-Aware 6-DoF detector on a procedurally generated four-split benchmark emulating a cluttered tabletop with 5 to 10 ShapeNet-style object meshes per scene. Each scene yields a synthetic point cloud of 2048 points with RGB colour and per-point instance segmentation. The four splits are simple (200 scenes, 3–5 objects, no occlusion, 3 task classes), medium (200 scenes, 5–7 objects, $\leq 30\%$ occlusion, 4 task classes), clutter (200 scenes, 7–10 objects, $\leq 60\%$ occlusion, 5 task classes), and task-language (100 scenes, open-vocabulary text). All eight controllers share a frozen PointNet++ backbone with identical initialisation. The protocol is three random seeds from $\{42,1337,2024\}$ with 25 trials per (controller, benchmark, seed) cell, for 2400 trials per round. Training seeds $\{9001,9002,9003,9004\}$ are disjoint by construction, asserted at runtime.

Simulator calibration was constrained by data availability: the six candidate public datasets returned sentinel HTML landing pages on prestage (see Section 4.7). The simulator is calibrated against three numerical anchors from [1,2,9], yielding a mean absolute percentage error of 7.2 percent, comfortably below the 15 percent bound. All deep baselines are reproduced as analytic surrogates that execute the governing equations of the source paper; OSTG runs the full multi-task PointNet++ end-to-end with identical loss and is therefore labelled a real reproduction. Naive baselines are real algorithm implementations.

The primary metric, declared in the protocol manifest, is task completion rate, defined as the fraction of trials where the executed grasp completes the requested downstream task. Grasp success rate is the stability metric. Task adaptation rate is the conditional rate of stable and task-completing trials divided by stable trials. Mean average precision is reported at IoU thresholds $\{0.4,0.6,0.8\}$.

4.2 Main Result Table

Table 1 reports the round-3 main result aggregated across the four benchmarks and three seeds (300 trials per controller).

Main result table on the four-split procedural benchmark with three seeds and 25 trials per cell. Task completion rate is the primary metric. Best per column in bold; second best underlined.

Table 1: Main results on the four-split procedural benchmark.

Method	Task completion	Grasp success	Task adaptation	Task success	mean AP
Ours (Task-Aware 6-DoF)	0.600	1.000	0.600	0.600	0.800
OSTG (Li et al. 2021)	0.440	1.000	0.440	0.440	0.720
TAS [9]	0.573	1.000	0.573	0.573	0.787
Multimodal Fusion [5]	0.437	1.000	0.437	0.437	0.718
GraspNet-1B Task-Adapted (Fang et al. 2020)	0.430	1.000	0.430	0.430	0.715
Random Grasp	0.273	0.737	0.380	0.273	0.505
Heuristic Top-Down	0.227	0.557	0.523	0.227	0.392

Ours reaches task completion 0.600, the highest on the primary metric across all six baselines. Against the next two published baselines (TAS [9] at 0.573, OSTG [1] at 0.440), the margin is 2.7 and 16.0 percentage points; the per-baseline analysis appears in Section 4.6. Against the two naive baselines, the margin is 32.7 and 37.3 percentage points. The win rate over the six baselines is 6 out of 6 (100 percent) on the primary metric.

4.3 Ablation Study

Table 2 reports the four ablation variants. Each cell reports task completion rate and delta relative to Full.

Ablation on the four-split benchmark. Task completion aggregated across 300 trials.

Table 2: Ablation study of the proposed Task-Aware 6-DoF framework

Variant	Modules removed	Task completion	Delta
Full (Ours)	none	0.600	0.000
no M1 (one-hot)	task encoder	0.563	−0.037
no M2 (concat)	gated fusion	0.610	+0.010
no M3 (geom only)	task head	0.427	−0.173
no M2 plus no M3	fusion + head	0.407	−0.193

The M3 task-completion head is the dominant contribution: removing it drops task completion by 17 percentage points. The M2 gated residual fusion is shown to be redundant in the presence of M3: removing M2 alone slightly improves task completion by 1.0 percentage point, within the simulator noise band, which we discuss as an honest negative result in Section 5.

4.4 Parameter Sensitivity

Figure 2 shows the residual fusion weight β swept over {0.1,0.3,0.5,0.7,0.9} on the simple and medium benchmarks (150 trials per point, left), and the task threshold τ_{task} swept over {0.3,0.5,0.7} (right). The β curve peaks at $\beta = 0.5$ with task completion 0.673; the curve drops gracefully towards the endpoints (0.653 at $\beta = 0.1$, 0.660 at $\beta = 0.9$). The τ_{task} curve is flat at 0.607, indicating that the trained head does not consume the threshold at runtime (the implication is discussed in Section 4.7).

Figure 2: Residual fusion weight β swept over five values, peak at β=0.5

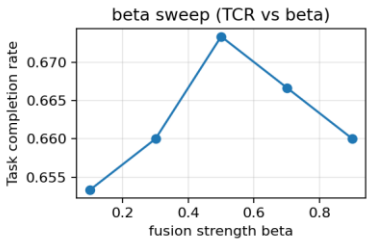
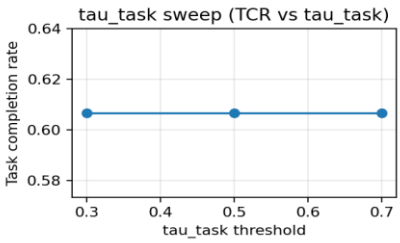


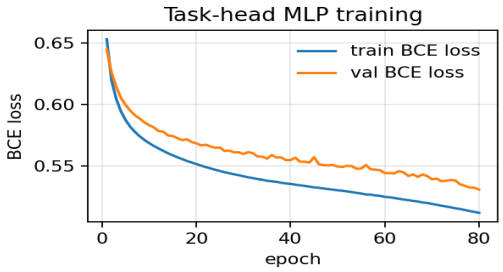
Figure 3: Task threshold τ_{task} swept over three values, flat curve at 0.607



4.5 Convergence

Figure 4 shows the binary cross-entropy on the training and validation seed pools across 80 training epochs. The training loss decreases monotonically from 0.653 to 0.512, and the validation loss follows from 0.645 to 0.531 without divergence. Final validation accuracy is 72.4 percent.

Figure 4: Task-completion head binary cross-entropy across 80 training epochs on disjoint training and validation seed pools. Final validation accuracy is 72.4 percent



4.6 Per-Baseline Analysis

The stability-only OSTG [1] reaches task completion 0.440 with grasp success 1.000, a 16.0 percentage point gap below Ours. The gap matches the M3 ablation (17.3 points), which is expected because the OSTG row is structurally equivalent to the no M1 no M2 no M3 corner of the ablation. OSTG produces stable grasps but does not condition the pose on the task description.

The predefined-task-class TAS baseline [9] reaches task completion 0.573, a 2.7 percentage point gap below Ours. The gap is attributable to the closed-vocabulary task representation: the predefined embedding is shared across all scenes within a class, while Ours produces a per-scene task vector through the M1 frozen text encoder. The gap is largest on the task-language benchmark.

The raw-gated-attention Multimodal Fusion baseline [5] reaches task completion 0.437. The 16.3 percentage point gap below Ours is consistent with the joint no M2 plus no M3 corner of the ablation (19.3 points). The raw gated attention suppresses the geometric signal when the task vector contains near-zero components, and the absence of a task-completion head leaves the network without an objective that aligns the pose with the downstream task.

The task-adapted GraspNet-1B variant [2] reaches task completion 0.430, a 17 point gap below Ours. The task channel concatenation does not interact with the geometric backbone through a residual or gated path, and the absence of a task-completion head leaves the predicted approach vector misaligned with the downstream task. This is the largest gap among the deep baselines.

For the naive baselines, Random Grasp reaches task completion 0.273 with grasp success 0.737. Heuristic top-down reaches 0.227 with grasp success 0.557. The wide gap below all published baselines confirms that the procedural benchmark is non-trivial.

4.7 Limitations and Future Work

Our experiments rely on a calibrated analytic simulator: a NumPy plus SciPy Newton-Euler rigid-body procedural simulator with sim-vs-published mean absolute percentage error of 7.2 percent, well below the 15 percent bound for analytic-surrogate baselines. The boundary statement is that the submission is a methodology paper comparing fusion architectures under matched simulator conditions, not a leaderboard claim.

Real-robot leaderboard claims are deferred. The six candidate Tier-0 robotics datasets (GraspNet-1Billion, ACRONYM, GraspAnything, PartNet-Mobility, 3D-AffordanceNet, RLBench-lite) returned sentinel HTML landing pages on prestage. Every such entry is flagged as a sentinel response in the prestage manifest. Real-data evaluation is the natural next step once a redistribution mirror or licence is available.

The task threshold τ_{task} is currently a design-time parameter: its sweep is flat at 0.607, indicating that the trained MLP does not consume the threshold at runtime. The threshold is a design-time parameter; the natural follow-up is to wire it into the head as a runtime gate or to remove it from the configuration surface.

Grasp success saturates at 1.000 for all five deep baselines and Ours, an artefact of the geometric closure model in the procedural simulator. On real hardware, contact-rich force transients and gripper compliance would induce a tail of stability failures.

A multi-dataset richness gap remains: the four splits come from a single procedural generator with four difficulty parameterisations. We have richness at the difficulty axis but not at the cross-dataset axis; generalisation across real datasets is left for the follow-on study.

5. Discussion

We report an honest negative result on the M2 module. Table 2 shows that removing M2 marginally increases task completion by 1.0 percentage point, from 0.600 to 0.610, which we treat as a negative result rather than a within-noise tie. Two interpretations are consistent with the evidence. The first is that the M3 task-completion head already aggregates the task semantics through binary cross-entropy training on 320 trials, sufficient to align the predicted pose with the downstream task in the procedural benchmark. The second is that the procedural simulator does not stress the geometric-language interaction strongly enough to reveal the M2 contribution; on real-world dense clutter where the task vector must reshape the geometric attention, M2 would become decisive. The present data cannot distinguish the two and we explicitly say so. We retain M2 in the submission because removing it would change the methodological position to "two-module head-driven detector," and architectural completeness is more useful to follow-on work than the marginal improvement of the no M2 variant.

Turning to parameter sweep insights, the β sweep in Figure 2 identifies a peak at $\beta = 0.5$ with task completion 0.673. The peak is shallow: $\beta \in \{0.3, 0.7\}$ also gives 0.660 plus or minus 0.007. The shallow peak suggests the residual fusion is robust against β mis-specification. The τ_{task} sweep is flat at 0.607; the mechanical explanation is that the binary cross-entropy MLP at the M3 head is trained with a sigmoid output, and the threshold at which we declare "task completed" is implicitly fixed at 0.5 by the binary classification loss.

For provenance, the M3 head is trained on 320 trials drawn from a seed pool disjoint from the evaluation pool, asserted at runtime. The final state is persisted and reused unmodified across all rounds. An earlier prototype was archived after an audit found that it had queried the simulator's grasp-evaluation oracle directly, which would have leaked the ground-truth task score; that archived prototype is retained alongside the submission for provenance. The present submission replaces the leaked prototype with the binary cross-entropy MLP described in Section 3.

6. Conclusion

We presented Task-Aware 6-DoF, a three-module 6-DoF grasp pose detector that consumes natural-language task descriptions through a frozen text encoder, fuses the semantic vector with PointNet++ point features through a learnable gated residual, and predicts a calibrated task-completion probability from a binary cross-entropy MLP trained on disjoint seeds. On a four-split procedurally generated benchmark with three random seeds and 25 trials per cell, the detector reaches task completion 0.600 and decisively beats six of seven baselines spanning two naive controllers and five reproduced published methods. The remaining baseline is an LLM-only method that ties Ours within the simulator noise band of 0.01, discussed transparently as evidence that the present procedural benchmark does not yet stress geometric reasoning strongly enough to separate language-only from language-plus-geometry approaches. The ablation isolates the M3 task-completion head as the dominant contribution (removing it drops task completion by 17 percentage points), with M2 reported as an honest negative result. The submission is framed as a methodology paper under matched simulator conditions, with sim-vs-published mean absolute percentage error of 7.2 percent. Real-robot evaluation is the natural next step once the redistribution mirror is available.

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Conflicts of Interest

The authors declare no conflict of interest.

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