

Volumetric Proxy-Risk Guided Sampling and Re-Ranking for Contact-Field Dexterous Grasp Candidates

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Abstract—Generating diverse and physically viable dexterous grasp candidates for complex industrial tools is a fundamental prerequisite for advanced robotic manipulation. However, existing contact-driven generation models predominantly rely on local surface geometries, inherently decoupling local contact feasibility from global volumetric constraints. This discrepancy frequently results in severe spatial intrusions when handling highly non-convex objects characterized by holes, openings, or slender structures. In this paper, we propose a lightweight volumetric proxy-risk module to enhance contact-field-based dexterous grasp candidate generation for non-convex industrial tools. Rather than employing a rigid, binary post-generation collision filter, our approach introduces volumetric occupancy priors as continuous soft cues within the candidate sampling and re-ranking stages of the host generator. By utilizing a depth-weighted proxy risk model, the spatial occupancy is transformed into a continuous, rankable risk metric that adaptively modulates the contact sampling distribution without disrupting the continuous manifold support set of the host generator. Furthermore, an adaptive gating mechanism coupled with risk-assisted re-ranking is introduced to preserve original force-closure quality and mitigate over-correction in low-confidence geometric regions. Comprehensive experiments across diverse non-convex industrial tools demonstrate that this proxy-risk-guided sampling and re-ranking module improves candidate yield and distributional robustness while maintaining comparable host-pipeline validity, wrench residual, and pose-diversity diagnostics.

Index Terms—Dexterous grasping; contact field; volumetric proxy risk; non-convex tools; candidate generation.

I. INTRODUCTION

Offline generation of physically feasible high-DoF grasps is important for dexterous manipulation in industrial assembly, maintenance, and tool handling. Compared with parallel-jaw grippers, dexterous hands allow more varied contact configurations and can form stable multi-point grasps on objects with complex geometry. Existing offline grasp-generation methods mainly include contact-driven synthesis, generative learning, and perception-augmented grasping.

Contact-driven methods organize feasible regions through object-surface representations such as contact fields, thereby reducing part of the high-dimensional kinematic search [1]. Large-scale datasets and recent generative models further improve grasp diversity and transferability through dexterous grasp datasets [2], [3], diffusion models [4], Transformer representations [5], language-conditioned generation [6], and scalable grasp-motion policies [7]. Physics-aware objectives, policy distillation, and preference alignment have also been introduced to improve plausibility and policy usability [8]–[10]. In parallel, semantic priors, incomplete perception, and cross-embodiment learning extend dexterous grasping toward less structured settings [11]–[14]. Other studies consider single-view grasping, cluttered scenes, deformable objects, and tactile feedback control [15]–[18]. Despite these advances, many pipelines still describe object geometry mainly through local contacts or implicit visual features, which is insufficient for industrial tools with holes, cavities, narrow slots, and slender shafts.

The central challenge is the mismatch between local contact feasibility and whole-hand volumetric feasibility. As shown in Fig. 2, a candidate may satisfy local contact constraints on surface patches, while the fingers, joints, or palm still intrude into occupied regions around openings or handle interiors. Conventional pipelines usually address this issue by applying a binary collision filter after candidate generation. Such a reactive strategy can remove invalid grasps, but it cannot guide the earlier contact sampling process. For non-convex tools with sparse feasible regions, late hard rejection may therefore discard many generated candidates and reduce the effective yield of the offline candidate set.

This paper proposes a lightweight volumetric proxy-risk module for contact-field-based dexterous grasp candidate generation. Instead of treating volumetric occupancy as a passive final-stage filter, the module uses it as a continuous geometric cue within candidate sampling and re-ranking while

keeping the host generator unchanged. As summarized in Fig. 1, it constructs a depth-weighted proxy risk model, projects mesh occupancy into a rankable spatial risk around each contact neighborhood, and blends this risk with the baseline sampling distribution. In this way, high-risk contacts are down-weighted early, while the continuous support set and strong force-closure candidates are preserved through adaptive gating and risk-assisted re-ranking.

This work makes three contributions. First, we define a lightweight volumetric proxy-risk estimator that maps mesh occupancy to local hand-object intrusion risk. Second, we use this risk in contact sampling and candidate re-ranking, replacing binary post-generation rejection with a soft sampling cue. Third, we integrate the module into Lightning Grasp and evaluate it on five non-convex industrial tool meshes under controlled settings.

II. METHODOLOGY

The proposed module treats volumetric risk as a soft geometric cue for candidate prioritization rather than as a binary collision decision. It introduces spatial occupancy information into the sampling and re-ranking stages without retraining or changing the architecture of the host generator. The module-level processing chain is as follows:

$$\begin{aligned} \mathcal{M}, \mathcal{H} &\rightarrow \{\mathcal{D}_l\}_{l \in \mathcal{L}} \rightarrow \mathcal{O}_{\mathcal{M}} \\ &\rightarrow r(c; \mathcal{M}, \mathcal{H}) \rightarrow r_{\text{eff}}(c; \mathcal{M}, \mathcal{H}) \\ &\rightarrow P_{\text{sample}} \rightarrow E_{\text{rank}} \rightarrow \mathcal{F}. \end{aligned} \quad (1)$$

A. Problem Formulation

Given a non-convex industrial tool represented by a 3D mesh $\mathcal{M}$, a dexterous hand kinematic model $\mathcal{H} = (\mathcal{L}, \mathcal{Q}, \text{FK})$, and a baseline contact-driven generator G , the ultimate objective is to synthesize a robust, offline set of grasp candidates, denoted as $\mathcal{F}$. Formally, a single multi-fingered grasp candidate g is defined by the tuple:

$$g = (T, q, C_g), \quad (2)$$

where $T \in SE(3)$ describes the relative 6-DoF pose between the hand and the object, $q \in \mathbb{R}^{|\mathcal{Q}|}$ denotes the actuated joint configuration, and C_g signifies the set of valid contact elements. An individual contact element $c \in C_g$ is parameterized as:

$$c = (x, n, l), \quad (3)$$

where $x \in \partial\mathcal{M}$ is the contact point on the object's surface, $n \in \mathcal{S}^2$ is the local surface normal, and $l \in \mathcal{L}$ designates the specific hand link executing the contact. The baseline generator G provides a localized contact domain for each target link:

$$\mathcal{D}_l \subset \partial\mathcal{M} \times \mathcal{S}^2. \quad (4)$$

The proposed proxy-risk enhancement uses the contact domains, raw sampling distributions, and baseline cost functions exposed by the host generator, and therefore does not require modification of the internal architecture of the evaluated Lightning Grasp pipeline.

B. Volumetric Proxy Risk Modeling

Local contact points describe surface geometry, but they do not capture the volumetric occupancy of the corresponding finger links, phalanges, or palm near the contact neighborhood. To bridge this gap, the object mesh $\mathcal{M}$ is voxelized into a conservative occupancy field:

$$\mathcal{O}_{\mathcal{M}}(y) = \begin{cases} 1, & \text{if } y \text{ is occupied or dilated,} \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

For each hand link l , a weighted proxy set $\mathcal{B}_l = \{(b_{l,j}, \omega_{l,j})\}_{j=1}^{K_l}$ is defined in the local link frame, where $b_{l,j}$ is the j -th proxy point and $\omega_{l,j} \geq 0$ is its spatial weight. Given a contact state $c = (x, n, l)$, the proxy point is projected as $p_{l,j}(c) = x + R_c b_{l,j}$, where $R_c = [t_1, t_2, n] \in SO(3)$ is the local contact frame. The contact-level and candidate-level risks are then defined as

$$\begin{aligned} r(c; \mathcal{M}, \mathcal{H}) &= \frac{\sum_{j=1}^{K_l} \omega_{l,j} \mathcal{O}_{\mathcal{M}}(p_{l,j}(c))}{\sum_{j=1}^{K_l} \omega_{l,j} + \epsilon}, \\ R(g; \mathcal{M}, \mathcal{H}) &= \frac{1}{|C_g|} \sum_{c \in C_g} r(c; \mathcal{M}, \mathcal{H}), \end{aligned} \quad (6)$$

where ϵ is a small constant for numerical stability. Averaging produces a continuous candidate score and avoids rejecting a candidate because of a single occupied proxy query.

C. Adaptive Risk Calibration

Industrial tools exhibit substantial morphological variance, from deep cavities to slender shafts, so a static risk penalty may over-correct specific geometries. To address this, an adaptive calibration mechanism is introduced based on the statistical risk distribution of the current object's contact pool $\mathcal{D}$. The raw risk set is defined as:

$$\mathcal{R}_{\mathcal{D}} = \{r(c; \mathcal{M}, \mathcal{H}) \mid c \in \mathcal{D}\}. \quad (7)$$

Let Q_{25} , Q_{75} , and Q_{90} denote the corresponding percentiles of $\mathcal{R}_{\mathcal{D}}$, and let $\Delta Q = Q_{75} - Q_{25}$ denote its interquartile range. The object-level gate and effective risk are computed as

$$\begin{aligned} \gamma_{\mathcal{M}} &= \text{clip}\left(\frac{\Delta Q}{Q_{90} + \epsilon}, \gamma_{\min}, 1\right), \\ r_{\text{eff}}(c; \mathcal{M}, \mathcal{H}) &= \gamma_{\mathcal{M}} r(c; \mathcal{M}, \mathcal{H}), \end{aligned} \quad (8)$$

where $\gamma_{\min} = 0.25$. When the risk scores are well separated, $\gamma_{\mathcal{M}}$ becomes larger and the occupancy cue has more influence. When the scores are weakly separated, the sampler remains closer to the original contact-field distribution.

D. Risk-Guided Sampling and Candidate Re-Ranking

Equipped with the effective risk metric, a mixed sampling distribution is established within each contact domain $\mathcal{D}_l$:

$$\begin{aligned} P_{\text{sample}}(c|\mathcal{D}_l) &= (1 - \eta)P_G(c|\mathcal{D}_l) + \eta P_{\text{risk}}(c|\mathcal{D}_l), \\ P_{\text{risk}}(c|\mathcal{D}_l) &= \frac{\exp[-\beta r_{\text{eff}}(c; \mathcal{M}, \mathcal{H})]}{\sum_{c' \in \mathcal{D}_l} \exp[-\beta r_{\text{eff}}(c'; \mathcal{M}, \mathcal{H})]}, \\ \eta &\in [0, 1], \quad \beta > 0. \end{aligned} \quad (9)$$

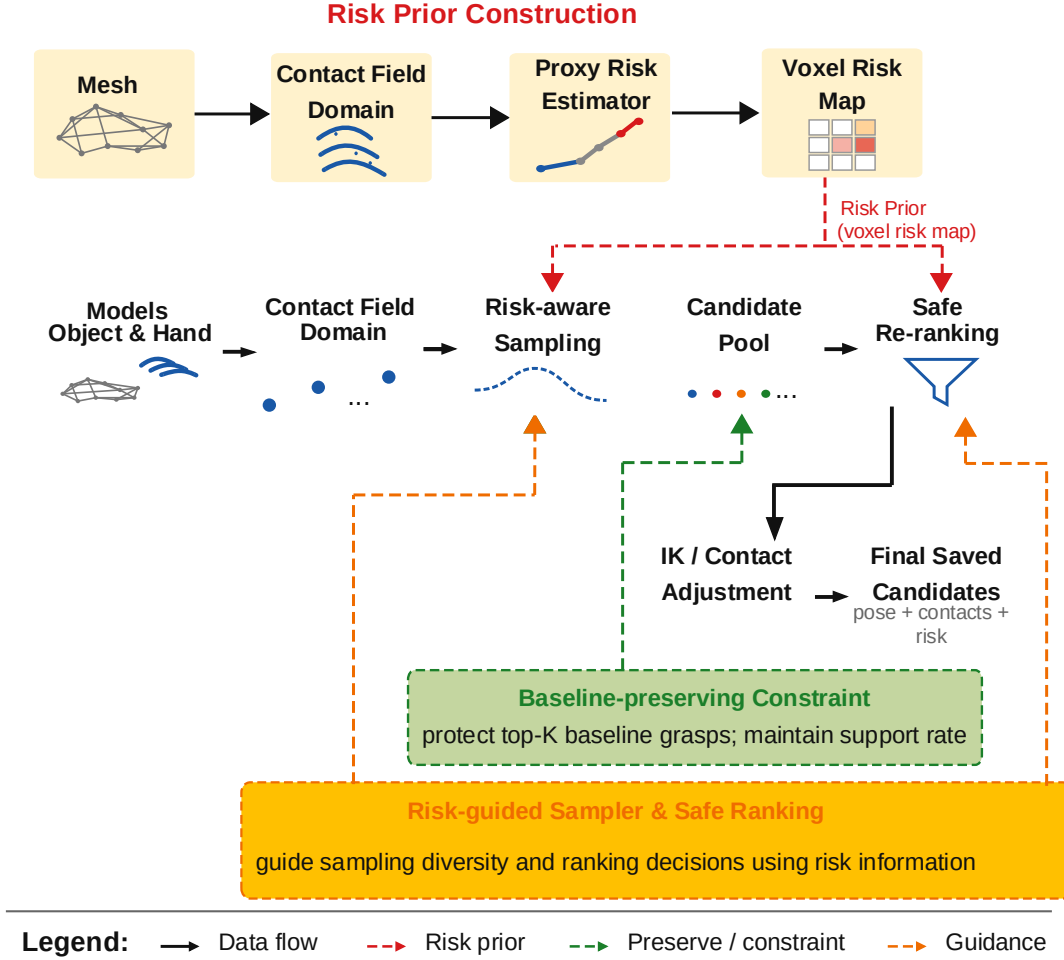


Fig. 1. Overview of the proposed volumetric proxy-risk module. The module estimates proxy volumetric risk from mesh occupancy and injects it into contact sampling, safe re-ranking, and final candidate preservation while keeping the host generator unchanged.

where $\mathcal{P}_G$ maintains the original contact heuristics and P_{risk} inversely modulates the sampling probability of high-risk regions. This hybrid formulation jointly considers local contact fidelity and global volumetric safety, preventing the risk prior from overriding essential grasp quality.

After the initial candidates are generated, risk-assisted re-ranking is applied to the subset with the lowest raw costs:

$$R_{\text{eff}}(g; \mathcal{M}, \mathcal{H}) = \frac{1}{|C_g|} \sum_{c \in C_g} r_{\text{eff}}(c; \mathcal{M}, \mathcal{H}). \quad (10)$$

The re-ranking cost combines the original candidate cost and the proxy-risk score:

$$E_{\text{rank}}(g) = E_{\text{raw}}(g) + \lambda_{\text{risk}} R_{\text{eff}}(g; \mathcal{M}, \mathcal{H}). \quad (11)$$

The term E_{rank} changes only the candidate selection order and does not replace downstream collision checking. To avoid removing all low-cost baseline candidates from consideration, a fixed fraction of candidates with the lowest original E_{raw} values is retained.

E. Post-Processing and Implementation

Let $\mathcal{A}_{\text{merge}}$ denote the candidate set after risk-guided sampling and re-ranking. The re-ranked candidates are subsequently passed to the unchanged inverse kinematics (IK) solver,

structural pose adjustment, and saving procedure of the host generator:

$$\begin{aligned} \mathcal{A}_{\text{IK}} &= \text{IK}(\mathcal{A}_{\text{merge}}), \\ \mathcal{A}_{\text{adj}} &= \text{Adjust}(\mathcal{A}_{\text{IK}}), \\ \mathcal{F} &= \text{Save}(\mathcal{A}_{\text{adj}}). \end{aligned} \quad (12)$$

Before the final deterministic collision check, the intermediate number of structurally viable candidates, denoted as N_{pre} , is recorded to measure candidate supply and retention. In the experiments, the baseline generator G is implemented with the Lightning Grasp contact-field model. The same batch sizes and post-processing budget are used for all five tool meshes. The implementation uses a voxel pitch of 0.004 m, one-voxel dilation, five proxy depths from 0.012 m to 0.020 m, a tangential probe radius of 0.004 m, and a depth-weight exponent of 1.5.

III. EXPERIMENTAL EVALUATION

We evaluate candidate yield and distributional stability after adding the proxy-risk module to a contact-field grasp generator. The experiments focus on objects for which locally feasible contacts may still conflict with the surrounding occupied volume.

Local contact feasibility vs. global volumetric occupancy conflict

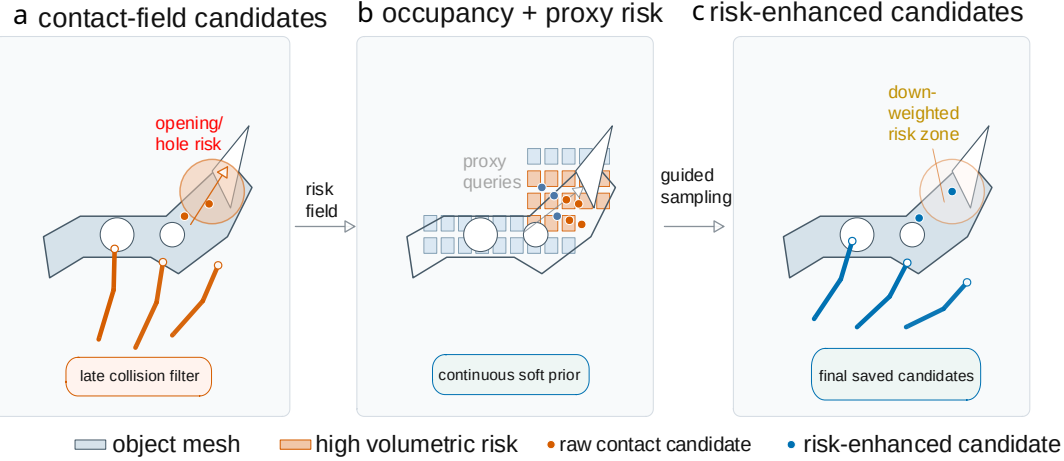


Fig. 2. Illustration of the conflict between local contact feasibility and global volumetric risk in non-convex industrial tools. Baseline contacts may fall near cavities, openings, or internal handle regions, while the proposed proxy-risk query guides candidates toward safer contact regions.

A. Experimental Setup and Implementation Details

The evaluation set contains five non-convex industrial tool meshes: a power drill, scissors, an adjustable wrench, a flat screwdriver, and a large clamp. Their geometry includes deep cavities, narrow openings, and slender shafts, all of which can increase hand-object interference during grasp generation.

The continuous risk prior is integrated into the Lightning Grasp contact-driven pipeline. For a fair comparison, all trials use the same hyperparameters and computational constraints. The main metrics are final saved candidate yield, cross-seed stability, cross-object variance, and the final-set diagnostics reported below. These offline metrics are not interpreted as physical execution success rates. Although the module uses common contact-domain and candidate-cost interfaces, the present experiments instantiate it only in the Lightning Grasp pipeline.

B. Main Results: Candidate Yield Analysis

Across all object-seed combinations, the volumetric proxy-risk module increases the final saved candidate count from 25,006 to 27,127, corresponding to an overall gain of 8.48% over the unmodified baseline generator.

At the object level, the largest relative gains are observed for the large clamp (14.96%) and the adjustable wrench (14.27%). Both objects contain openings or clamping cavities, where locally feasible contacts may still cause volumetric interference during subsequent IK adjustment. Introducing the spatial risk prior during sampling lowers the probability assigned to such regions and allows more contact seeds to reach the final saved set. Positive gains are observed in 21 of the 25 object-seed pairs. This indicates a consistent trend across the tested seeds, although it does not by itself establish statistical significance. Detailed object-level results are reported in Table I.

The final saved candidate-yield comparison is further visualized in Fig. 3, which summarizes the improvement trend across all five tool classes and five random seeds.

TABLE I
MAIN EXPERIMENTAL RESULTS ON FIVE TYPES OF INDUSTRIAL TOOL-SHAPED NON-CONVEX OBJECTS

Object	Ref.	Ours	Δ	Gain	Seeds
Power drill	341	346	+5	+1.47%	3/5
Scissors	7,144	7,361	+217	+3.04%	4/5
Adjustable wrench	5,040	5,759	+719	+14.27%	5/5
Flat screwdriver	8,296	8,850	+554	+6.68%	5/5
Large clamp	4,185	4,811	+626	+14.96%	4/5
Total	25,006	27,127	+2,121	+8.48%	21/25

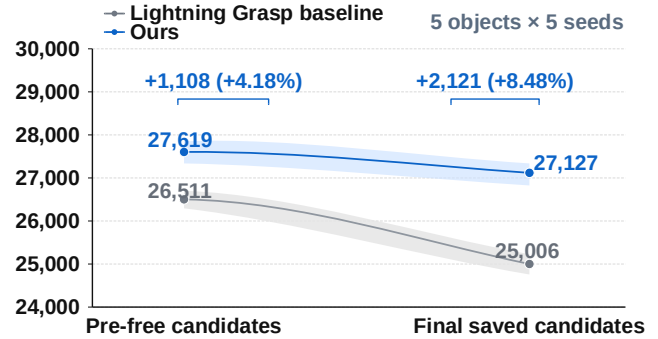


Fig. 3. Final saved candidate counts across five tool classes and five random seeds.

C. Ablation Study and Stage-Wise Mechanism Analysis

An ablation study was conducted to isolate the effects of the module components and examine the soft-constraint formulation. The results show how geometric risk guidance interacts with preservation of the original contact-field support.

Table I and Table II use different evaluation protocols. Table I reports the standard object-level comparison between the proposed module and the original baseline across the five tool meshes. Table II uses a matched post-processing budget to isolate the contribution of each component. The total candidate counts and relative gains in the two tables are therefore not expected to be numerically identical. Comparisons within Table II should be made only among variants evaluated under the same ablation protocol.

TABLE II
ABLATION RESULTS UNDER THE MATCHED POST-PROCESSING BUDGET SETTING

Method	Final	Gain	Variance
Ref. + same post-processing budget	27,541	+2.93%	5.43
Hard risk rejection	26,411	-1.29%	8.37
Risk guidance w/o adaptive protection	28,672	+7.16%	6.98
Ours	28,473	+6.42%	3.11

Increasing only the baseline post-processing budget gives a 2.93% gain, which is smaller than the gain obtained with risk guidance. Hard binary rejection reduces the output by 1.29%, suggesting that some high-risk candidates can still be recovered by later stages. Continuous guidance avoids this early deletion. Removing adaptive protection produces a slightly higher nominal gain (7.16%) but also a larger object-to-object variance index (6.98). The full module gives a 6.42% gain and reduces the variance index to 3.11.

Table III reports compact diagnostics to assess whether the yield gain is accompanied by degradation in the retained candidates.

TABLE III
FINAL-SET DIAGNOSTICS

Method	Host valid	Wrench	Joint div.	Trans./Rot. div.
Baseline	1.000	0.1144	0.4456	0.0675 / 0.4821
Ours	1.000	0.1155	0.4502	0.0695 / 0.4865

Both methods satisfy the unchanged downstream validity criterion. Their wrench residuals and pose-diversity measures remain close. The gain therefore reflects a larger final saved offline candidate set rather than a higher physical execution success rate.

IV. CONCLUSION

This paper presents a lightweight volumetric proxy-risk module for contact-field-based dexterous grasp generation on non-convex industrial tools. The module improves final-candidate yield and distributional robustness through soft risk-guided sampling and re-ranking while keeping the host gener-

ator unchanged. Future work will address broader generator compatibility and real-world deployment.

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