Project Proposal

Advanced Deep Learning for Robotics [CIT433027]

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I. Objective

This research project focuses on training a grasp quality score predictor to serve as an objective function for online grasp optimization. Building upon existing methods that primarily utilize binary grasp-success classifiers, our approach uses a differentiable grasp quality scoring network. By differentiating through this network, grasp parameters are optimized to maximize the predicted quality score, thereby enabling more nuanced grasp evaluation beyond simple success predictions.

The hypothesis underlying this project is that grasp quality scores provide richer, detailed feedback on grasp nuances, potentially identifying more optimal grasp configurations.

Additionally, the project will explore enhancing the grasp proposal process through training a generative model capable of suggesting initial grasp candidates.

Furthermore, we may consider architectures such as DINO-WM [1] for trajectory based grasp planning with model predictive control (MPC).

Finally, if time permits, we will evaluate our approach against existing state-of-the-art grasp optimization methods, such as DiGrasp, to assess its effectiveness and relative performance.

II. Related Work

Early work such as Dex-Net 2.0 showed that large-scale synthetic data and a Grasp-Quality CNN can predict the success of pre-sampled parallel-jaw grasps with high reliability, laying the foundation for score-based grasp planning. [2]

For multi-fingered hands, Winkelbauer et al.'s two-stage architecture introduces a dataset of 18-DoF grasps with continuous quality labels and shows that a learned score can drive a second-stage optimiser toward higher-quality configurations. [3]

Van der Merwe et al. push this idea further by coupling a learned 3-D reconstruction with a differentiable success predictor, enabling direct gradient ascent in grasp space while enforcing collision-free geometry. [4]

Recent planners such as DiPGrasp make the optimisation itself fully differentiable, combining analytical force-closure metrics with parallel gradient search for fast convergence on arbitrary grippers. [5]

Complementary generative approaches—e.g., the latent-diffusion-based GraspLDM—sample diverse 6-DoF candidates that can be re-ranked by any quality metric. [6]

Our project unifies these threads: we learn a differentiable quality network from Winkelbauer's dataset and maximise its score to refine grasps online, optionally seeding the search with a lightweight generative prior.

III. Technical Outline

For the duration of the project, we plan to follow the following steps in order.

1) **Preprocessing.** Getting familiar with the dataset of multi-finger grasps. Then, preprocess the dataset by filtering out low-quality samples, removing outliers, and normalizing point cloud data for consistent training.
2) **Stable grasp computation.** Given a point cloud or a voxel grid of an object, use geometric and physical constraints to identify candidate grasps that ensure mechanical stability during manipulation.
3) **Grasp quality score function.** Train a neural network or statistical model to estimate the quality of proposed grasps, quantifying their likelihood of success based on stability criteria and contact points.
4) **Iterative grasp refinement.** Employ optimization methods, such as gradient descent or other optimization methods, to iteratively adjust grasp configurations by minimizing the learned quality score, thereby improving grasp robustness.
5) **Optional: Generative model for grasp proposals.** Train a generative model (e.g., Variational Autoencoder, GAN, or Diffusion models) to efficiently propose initial grasp configurations that can accelerate the optimization process.
6) **Optional: MPC with DINO-WM.** Leverage the Dynamics-Informed Neural Optimizer (DINO-WM) within a Model Predictive Control (MPC) framework to compute optimal trajectories from grasp initiation to final stable post-grasp states.
7) **Optional: Evaluate trajectory endpoints.** Utilize a learned grasp-quality prediction network to evaluate the predicted final states from computed trajectories, ensuring that grasp endpoints meet desired stability criteria.
8) **Optional: Benchmark comparison.** Conduct comprehensive evaluations by comparing the developed method against existing state-of-the-art approaches such as DiP-Grasp, to validate performance improvements in stability, efficiency, and generalization.

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