Learning Grasp Evaluation Models Using Synthetic 3D Object-Grasp Representations

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1 Publishable Results

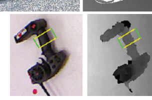
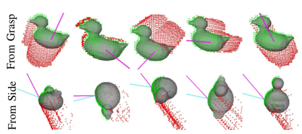
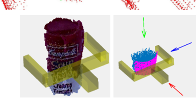
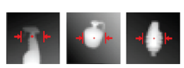
Method	Object-grasp representation	Feature extraction & learning model	Data generation
[2]		Histogram of hand-crafted filters; Model: SVM.	Rectangles manually annotated.
[4]		Auto-encoders to initialize weights, structured regularization to combine depth and RGB data; Model: MLP.	Extension of the dataset from [2] (above).
[3]		RGB rendering of “template grids”; Model: LeNet CNN	Quality of grasps are calculated in simulation for object meshes, verified via crow-sourcing.
[1]		Filters of cuboid regions projected onto 3 orthogonal planes, creating 15 channels; Model: LeNet CNN.	Quality of grasps are calculated for object meshes using force-closure
[5]		Depth images cropped and aligned to gripper; Model: CNN combined with single-layer NN.	Quality of grasps are calculated for object meshes using a variant of ϵ-metric from [9]

Table 1. Five recent empirical approaches to grasp quality prediction

The first contribution of this work is a detailed review of recent advances in aspects most relevant to generating data for training a grasp evaluation models, namely feature extraction from perceptual data, object-grasp representation, grasp evaluation metrics, and data generation techniques. Additionally, five recent, prominent approaches to data synthesis for grasp evaluation are examined, and their solutions for each of the four aspects mentioned above are summarized in table 1.

The second contribution of this project is the implementation of a full grasping pipeline, from perceiving objects to grasp execution, in collaboration with another Research and Development project by Padalkar [6]. Two pose estimation methods are implemented, serving as baselines for experimenting and comparing with more advanced grasp planning techniques.

The review of recent approaches to grasp data synthesis demonstrates their limitations either in dataset size or by using theoretical approaches to generate data labels, suggesting possible extensions and improvements with larger human grasp experience database [7] or more advanced feature extraction methods [8].

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