Generating Grasp Poses for a High-DOF Gripper Using Neural Networks

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Abstract—We present a learning-based method to represent grasp poses of a high-DOF hand using neural networks. Due to the redundancy in such high-DOF grippers, there exists a large number of equally effective grasp poses for a given target object, making it difficult for the neural network to find consistent grasp poses. We resolve this ambiguity by generating an augmented dataset that covers many possible grasps for each target object and train our neural networks using a consistency loss function to identify a one-to-one mapping from objects to grasp poses. We further enhance the quality of neural-network-predicted grasp poses using a collision loss function to avoid penetrations. We use an object dataset combining the BigBIRD Database, the KIT Database, the YCB Database, and the Grasp Dataset, on which we show that our method can generate high-DOF grasp poses with higher accuracy than supervised learning baselines. The quality of grasp poses are on par with the groundtruth poses in the dataset. In addition, our method is robust and can handle noisy object models, such as those constructed from multi-view depth images, allowing our method to be implemented on a 25-DOF Shadow Hand hardware platform.

I. INTRODUCTION

Grasp pose generation and prediction is an important problem in robotics [33], [32]. Recently, learning-based methods [21], [17], [18] have achieved a high rate of success in terms of grasping unknown objects. However, these methods are mainly limited to low-DOF grippers with only 1-6 DOFs or they assume that a high-DOF gripper moves in a low-DOF subspace [6]. This assumption limits the space of the grasp poses a robot hand can represent and the space of the target objects the hand can handle. In this work, we address the problem of developing learning algorithms for generating grasp poses for a high-DOF hand. Such high-DOF hands have been used to perform complex in-hand manipulations in prior works [2], [28].

Generating grasp poses for a high-DOF gripper is more challenging than for low-DOF grippers due to the existence of pose ambiguity, i.e., there exists a large number of equally effective grasp poses for a given target object. However, we need to train a single neural network to predict one grasp pose for each object. As a result, we need to pick a set of grasp poses for a set of target objects, that can be represented by the neural network. In the case of a low-DOF gripper, if the neural network predicts the correct direction and orientation towards the object, one can simply close the gripper and the predicted grasp operation will very likely be successful. Therefore, most prior works [21], [35], [6] only learn the approaching direction and orientation of the gripper. For high-DOF gripper, however, there are multiple remaining DOFs (beyond direction and orientation) to be determined after the wrist pose is known. Computing these remaining DOFs is still a major challenge in the deep-learning-based grasp pose generation methods.

There are two kinds of learning-based methods for grasp pose generation. In the first type of methods [18], [9], a grasp pose is generated using two steps. First, a neural network is trained to predict the possibility of success given a grasp pose as an input. Second, the grasp pose is generated during runtime using a sampling-based optimizer, such as multi-armed bandit [22], to maximize the possibility of success. This method does not suffer from pose ambiguity by allowing multiple grasps to be equally effective for a single object. However, the high-DOF nature of the gripper results in a large search space for the sampling-based optimizer, making the online phase very computationally costly. In the second kind of methods [6], a neural network is trained to predict the grasp poses directly from single-view observations of the object. As a result, this direct method becomes very efficient because only a forward propagation through the neural network is needed to generate the grasp pose. However, since many high-DOF grasp poses can be equally effective for a single object, an additional constraint is required to guide neural networks to determine the poses from which it should learn. Due to the lack of such guidance, [6] can not be used to directly generate high-DOF grasp poses.

Main Results: We present a learning-based method for representing grasp poses for a high-DOF articulated robot hand. Our method enables fast grasp pose generation without the low-DOF assumption. Similar to [6], we train a neural network to predict grasp poses directly so that grasp poses can be generated efficiently during runtime. To resolve the ambiguity of grasp poses for each object, we introduce the notion of consistency loss, which allows the neural network to choose from a large number of candidate grasp poses and select the one that can be consistently represented by a single neural network. However, the grasp poses predicted by the network can be in close proximity to the object, leading to many hand-object penetrations. To resolve this issue, we introduce collision loss, that penalizes any robot-object penetrations, to push the gripper outside the object. We train the neural network for 40hr on a dataset of 324 objects by combining the BigBIRD Database [31], the KIT Object Models Database [14], the YCB Benchmarks [5], and the Grasp Database [13]. We show that our method can achieve...
4× higher accuracy (in terms of distances to the groundtruth grasp poses) than supervised learning baselines in grasp pose representation. In addition, we show that our method can be used in several application scenarios by taking inaccurate 3D object models as input; these object models are reconstructed from multi-view depth images. As a result, our method can be implemented on a 25-DOF Shadow Hand hardware, as shown in Figure 1, where each grasp can be computed within 3-5 seconds at runtime.

The rest of the paper is organized as follows. We review related work in Section II and then formulate our problem in Section III. The main neural network architecture and training algorithm are presented in Section IV. Finally, we highlight the performance on different objects in Section V.

II. RELATED WORK

Methods for robot grasp pose generation can be classified based on the assumptions that make about the inputs. Early works [36], [23], [3], [24] are designed for complete 3D shapes, such as 3D triangulated meshes of objects, as input. To estimate the quality of a grasp pose [36], [23] or compute a feasible motion plan [3], [24] deterministically, a 3D mesh representation is used. However, these methods are difficult to deploy on current real-world grasping systems or robot hands due to discrepancy and sensing uncertainty. Most practical grasp planning methods that can take incomplete shapes are based on machine learning. Early learning methods predict good grasp poses [11] or points [30] from several RGB images using manually engineered features and supervised/active learning [25]. More recently, learning-based grasp pose prediction algorithms [22], [21], [18], [6], [4], [12], [27] replace manually engineered features with features learned from deep convolutional networks for better generality and robustness. All these methods are designed for low-DOF grippers. Some learning-based methods [1], [34] take an incomplete or a partial shape as input and reconstruct a voxelized shape internally. Our method uses [24] to generate groundtruth grasping data, and we assume that the input to the neural-network is a complete object model represented using an occupancy grid. However, our trained network is robust to data inaccuracies and can be applied to object models reconstructed from multi-view depth images.

Most existing learning-based methods [11], [22], [21], [18], [6], [19] use the learned model in a two-stage algorithm. During the first step, the learned neural network takes both the observation of the object and a proposed grasp pose as an input and predicts the possibility of a successful grasp. During the second step, the final grasp pose is later optimized to maximize the rate of success using exhaustive search [11], gradient-based optimization [19], [20], sampling-based optimization [18], or multi-armed bandits [22]. Instead, our method uses a learning model to predict the grasp poses for a high-DOF gripper directly. Our method is similar to [6], which learns a neural network to predicts the grasp poses directly, but [6] is designed for low-DOF grippers as pose ambiguity is not handled.

III. PROBLEM FORMULATION

In this section, we formulate the problem of high-DOF grasp pose generation. Each grasp pose is identified with a high-DOF configuration \( \mathbf{x} = (\mathbf{x}_b^T \mathbf{x}_j^T)^T \) of the robot hand, where \( \mathbf{x}_b \) is the 7-DOF rigid transformation of the hand wrist and \( \mathbf{x}_j \) is the remaining DOFs, i.e., joint angles. Our goal is to find a mapping function \( f(o) = x \), where \( o \) is an observation of the object \( O \). This observation can take several forms. In this paper, we assume that \( o \) is the 3D occupancy grid [7], [10] derived by discretizing the object. We denote \( o_s \) as the signed distance field [26] derived by solving the Eikonal equation from the original mesh.

We use deep neural networks to represent \( f \) with optimizable parameters denoted by \( \theta \). The main difference between our method and prior deep-learning-based methods [34], [9], [22] is that our network directly outputs the
grasp pose \( x \). Prior methods only predict the possibility of successful grasps, given a possible grasp pose, which can be summarized as a function \( g(x, o) = p \), where \( p \) is the possibility of success. Function \( g \) has advantages over our function \( f \) because \( g \) allows multiple versions of \( x \) to be generated for a single \( O \). However, in order to use \( g \), we need to solve the following problem:

\[
\arg\max_x g(x, o),
\]

which can be computed efficiently for low-DOF grippers, using either sampling-based optimization [18] or multi-armed bandits [22]. But this optimization can be computationally costly for a high-DOF gripper due to the high-dimensional search space. This optimization can also be ill-posed and under-determined, because many unnatural grasp poses might also lead to effective grasp poses as shown in [8]. This is our main motivation for choosing \( f \) over \( g \). However, training a neural network that represents function \( f \) is more challenging than training \( g \) for two reasons.

- If we have a dataset of \( N \) objects and groundtruth grasp poses \( \{ O_i, x_i \} \), a simple method of training is to use the data loss \( \mathcal{L}_{data} = \sum_i \| f(o_i, \theta) - x_i \|^2 \). However, since multiple grasp poses \( x \) are valid for each object \( O \), we can build many datasets for a same set of objects \( \{ O_i \} \) by choosing different grasp poses for each object. The resulting data loss \( \mathcal{L}_{data} \) generated by using different datasets can be considerably different according to our experiments. Therefore, the first challenge in training function \( f \) is that we need to build a dataset leading to a small \( \mathcal{L}_{data} \) after training.

- As a second problem in training \( f \), we have to ensure the quality of grasp poses generated by the neural networks. The quality of a grasp pose in learning-based methods can be measured by comparing it with the groundtruth pose. But there are other important metrics. For example, a grasp pose should not have penetration with \( O \). In prior methods [34], [9], [22], the neural network is not responsible for ensuring the quality of the grasp poses, and we can guarantee the high quality of grasp poses when solving Equation 1 after training. However, in our case, the neural network is used to generate \( x \) directly, so that our final results is very sensitive to the outputs of the neural network.

IV. LEARNING HIGH-DOF GRASP POSES

In this section, we present the architecture of our neural network used for high-DOF grasping.

A. Neural Networks

We represent \( f \) using a deep neural network, as illustrated in Figure 2. We assume that a high-DOF grasp pose can be generated from a low-dimensional feature vector of the object denoted by \( \omega \), a similar approach is used by [6]. We use a fully connected sub-network \( \text{NN}_x \) to parameterize this mapping function:

\[
x = \text{NN}_x(\omega, \theta_1),
\]

where \( \theta_1 \) is the optimizable weights. To parameterize \( \text{NN}_x \), we use a network with 3 hidden layers with \((64 \times 7 \times 7 =) 21952, 4096, 1024\) neurons, respectively. We use ReLU activation functions for each hidden layer and we add batch normalization to the first two hidden layers. When different sensors leading to different observations of \( O \) are used in our application, such as an occupancy grid or a depth image, we use another sub-network to transform the observation to \( \omega \). Therefore, we have:

\[
\text{NN}_o(o, \theta_3) = \omega,
\]

and \( \theta = (\theta_1^T \theta_2^T \theta_3^T)^T \). This neural network is fully convolutional. \( \text{NN}_o \) has 3 3D-convolutional layers with 64 kernels of size 4. We add batch normalization, ReLU activation, and max-pooling layers after each convolutional layer. Finally, we have \( f = \text{NN}_x \circ \text{NN}_o \).

B. Consistency Loss

In practice, optimizing \( \theta \) is difficult due to the two challenges discussed in Section III. We resolve these issues using two loss functions. Our first loss function is called a consistency loss function which is used to resolve the grasp pose ambiguity for each \( O \). Instead of picking one grasp pose \( x \) for each \( O \) during dataset construction, we compute a set of \( K \) grasp poses denoted by \( x_{i,j} \) for each \( O_i \), where \( j = 1, \ldots, K \), resulting in a large dataset with \( NK \) grasp poses for \( N \) objects. As a result, our consistency loss function takes the following form:

\[
\mathcal{L}_{consistency} = \sum_{i,j} \min_j \| f(o_i, \theta) - x_{i,j} \|^2 / N.
\]

This novel formulation allows the neural network to pick the \( N \) grasp poses leading to the smallest residual. Note that, although \( \mathcal{L}_{consistency} \) is not uniformly differentiable, its subgradient exists and optimizing \( \mathcal{L}_{consistency} \) with respect to both \( \theta \) and \( j \) can be performed with the conventional backpropagation gradient computation framework [15]. Specifically, after forward propagation computes \( f(o_i, \theta) \) for every \( i \), we pick \( j \) leading to the smallest residual, and finally perform backward propagation with:

\[
\frac{\partial \mathcal{L}_{consistency}}{\partial f(o_i, \theta)} = (f(o_i, \theta) - x_{i,j}) / N
\]

\[
\hat{j} = \arg\min_j \| f(o_i, \theta) - x_{i,j} \|^2.
\]

C. Collision Loss

To resolve the second challenge and ensures the quality of learned grasp poses, we notice that most incorrect or inaccurate \( x \) predicted by the neural network have the gripper intersecting with \( O \). To resolve this problem, we add a second loss function that penalizes any penetrations between the gripper and \( O \). Specifically, we first construct a signed distance function \( o_s \) from the original mesh, and then sample a set of points \( p_{s=1, \ldots, P} \) on the gripper. Next, we formulate the collision loss function as:

\[
\mathcal{L}_{collision} = \sum_{i=1}^P \min_j (o_s(T(p_i, f(o_i, \theta))), 0),
\]

where \( T \) is the forward kinematics function of the gripper transforming \( p_i \) to its global coordinates. We also assume \( o_s \) has positive values outside \( O \) and negative values inside.
Fig. 2: An illustration of our two sub-networks (a): $\mathbf{N}N_o$ maps the observations of the object to the feature vector $\omega$. (b): $\mathbf{N}N_x$ maps the feature vector $\omega$ to the grasp pose $x$. We use the same network architecture for different robot hand hardwares with different DOFs, by modifying only the output layer.

\( \beta \). Again, $L_{\text{collision}}$ is not uniformly differentiable but has a well-defined sub-gradient, so it can be used to optimize the neural network. In our experiments, we found that the quality of learned grasp poses is sensitive to the selection of sample points $p_i$. We choose to use the same set of sample points for dataset generation and the collision loss function. Specifically, we use simulated annealing [8] to generate groundtruth grasp poses. [8] optimizes an approximate grasp quality function that measures the distance between a set of desired contact points to the object surfaces. These contact points are also used as sample points in $L_{\text{collision}}$.

D. Combined Loss

The consistency loss and the collision loss are combined using parameter $\beta$ as shown in the following equation:

$$L_{\text{combined}} = \beta \cdot L_{\text{consistency}} + (1 - \beta) \cdot L_{\text{collision}},$$

(2)

where the relative weight $\beta$ is between 0 and 1. Empirically, we find that higher value of $\beta$ results in grasps that are more natural looking, while a lower value of $\beta$ brings fingers closer to the surfaces of objects, which in turn results in higher success rates.

E. Pose Refinement

After a neural network predicts a nominal grasp pose for an unknown, we can further refine it at runtime by looking for another grasp pose that is close to the nominal pose but does not have any intersections with the object. To do this, we solve a simple optimization. Specifically, after the neural network predicts $f(o, \theta)$, we first search for another pose $x^*$ closest to it that further minimizes our objective function:

$$\arg\min_{x^*} \beta \cdot \| x^* - f(o, \theta) \|^2 + (1 - \beta) \cdot L_{\text{collision}}.$$ 

We call this procedure pose refinement.

V. IMPLEMENTATION AND PERFORMANCE

In this section, we provide more details about our experiment platform setup, results, and evaluations.

A. Grasp Training Dataset Generation

Given a set of target objects, we take three steps to generate our grasp pose training dataset. First, we use an existing sampling-based motion planner, GraspIt! [24], to generate many high quality grasp poses for each object. We then perform data augmentation via global rigid transformation. Finally, we compute a signed distance field for each of the target objects.

1) Grasp Pose Generation: We collect object models from several datasets, including BigBIRD [31], KIT Object Models Database [14], YCB Benchmarks [5], and Grasp Database [13]. Our dataset contains $N = 324$ mesh models, of which most are everyday objects. Our high-DOF gripper is the Shadow Hand with 25 DOFs, as shown in Figure 3. Given an initial pose of the Shadow Hand, GraspIt! uses an optimization-based planner to find an optimal grasp pose that minimizes a cost function, which is found via simulated annealing. The cost function can take various forms and we use the sum of distances between sample points and object surfaces as the cost function. We run simulated annealing for 10000 iterations, where the planner generates and evaluates 10 candidate grasp poses during each iteration. To generate many redundant grasp poses for each object, we run the simulated annealing algorithm for $K = 100$ times from random initial poses. Altogether, the groundtruth grasp pose dataset is generated by calling the simulated annealing planner $324 \times 100$ times. Some grasp poses for an object are illustrated in Figure 4.

Fig. 3: Left: the Shadow Hand model we use and the sampled potential contact points in blue. Right: the real Shadow Hand.

Fig. 4: An illustration of some sample grasp poses (yellow) for a single object (gray).

Fig. 4: An illustration of some sample grasp poses (yellow) for a single object (gray).
2) Data Augmentation: Generating groundtruth grasp poses using motion planner is very computationally costly, so we use a simple method to synthesize more data. The input to $\text{NN}_v$ is a voxelized occupancy grid. We move the objects and put their center of mass to the origin of the Cartesian coordinate system, and then rotate each object along with its 100 best grasp poses along 27 different rotation angles and axes. These 27 rotations are derived by concatenating rotations along X, Y, Z-axis for $60^\circ$, $120^\circ$, $180^\circ$, as illustrated in Figure 6. For each rotation, we record the affine transformation matrix $T_r$. In this way, we generate a dataset that is 27 times larger. This data augmentation not only helps resist over-fitting when training neural networks but also helps make the neural network invariant to target object poses.

![Fig. 5: An illustration of rotated object poses and grasp poses generated by data augmentation.](image)

3) Signed Distance Fields Construction: To calculate the collision loss when training our neural networks, we compute a signed distance field $G_{sd}$ for each target object by solving the Eikonal equation. We set the resolution of $G_{sd}$ to $128^3$ and $G_{sd}$ has a local coordinate system where $G_{sd}$ occupies the unit cube between $[0,0,0]$ and $[1,1,1]$. If the maximal length of the object’s bounding box is $L$, the transformation matrix from an object’s local coordinate system to $G_{sd}$’s local coordinate system is:

$$T_{sd} = \begin{bmatrix} s & 0 & 0 & 0.5 \\ 0 & s & 0 & 0.5 \\ 0 & 0 & s & 0.5 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad s \geq 0.95/L,$$

which is illustrated in Figure 6.

![Fig. 6: Signed distance fields construction, where the green area is the domain of $o_n$.](image)

B. Experimental setup

We split the set of 324 target objects into a 80%(259) training set and a 20%(65) testing set. Note that each object mesh is augmented to 27 meshes with different $T_r$. After we voxelize the meshes into 3D occupied grids, we get a total of $324 \times 27 = 8748$ grids, each with a related $T_r$. All augmented meshes related to the same object share the same $G_{sd}$. Transformation from augmented meshes to $G_{sd}$ is given as $T_{sd} \cdot T_r^{-1}$. On the Shadow Hand, we sample $P = 45$ potential contact points, as shown in Figure 3. To sample the signed distance field using $T(p_i, f(o_i, \theta))$, we need to transform the point from the global coordinate system to the coordinate system of the signed distance field, which is:

$$T_{sd} \cdot T_r^{-1}(p_i, f(o_i, \theta)).$$

As shown in Figure 7. All experiments are carried out on a desktop with an Intel® Xeon W-2123 @ 3.60GHz × 4, 32GB RAM and an NVIDIA® Titan Xp graphics card with 12GB memory, on which training the neural networks take 40 hours.

C. Results and evaluation

In this section, we evaluate the performance of our method and demonstrate the benefits of our novel training method for solving high-DOF grasp problems.

1) Challenge of High-DOF Grasp Problems: In our first benchmark, we highlight the challenges of dealing with high-DOF grippers and the necessity of our novel loss function for solving the problem. We first train our neural network using conventional supervised learning. In other words, we create a small dataset with each object corresponding to only one grasp pose ($K = 1$), and we use the simple $L_2$ loss function:

$$L_2 = \sum_i |f(o_i, \theta) - x_i|^2/N.$$

With this loss function, we train two neural networks to represent grasp poses for both a high-DOF gripper (25-DOF Shadow Hand) and a low-DOF gripper (11-DOF Barrett Hand) and compare the residual of $L_2$ after training. Due to the pose ambiguity, supervised learning using the $L_2$ loss function can lead to inconsistency problems. Our experimental results in Table I also show that this inconsistency problem is more serious in high-DOF grippers. These two neural networks are trained using the ADAM algorithm [16], with a fixed learning rate of 0.001, a momentum of 0.9, and a batch size of 16.

| Hand    | DOFs of Grippers | Residual of $L_2$ on Test Set | Residual of $L_2$ on Training Set |
|---------|------------------|-------------------------------|----------------------------------|
| Shadow  | 25               | 73.61                         | 76.02                            |
| Barrett | 11               | 5.84                          | 4.76                             |

TABLE I: We train two neural networks using an $L_2$ loss function to represent grasp poses for the Shadow Hand and the Barrett Hand. The residual is much higher for the Shadow Hand on both the training set and the test set, meaning that high-DOF grippers suffer more from the inconsistency problem, that can be resolved using the consistency loss function.

2) Consistency and Collision Loss: As shown in Table II, we train the neural network using our large dataset with $K = 100$. In this experiment, we train three neural networks using two different loss functions, $L_{\text{consistency}}$ and $L_{\text{combined}}$, where we pick $\beta = 0.75$. After training each neural network, we evaluate it on the test set and summarize the residuals.
of different losses, leading to 6 values in Table II; we also copy the first row of Table I to Table I as a reference of simple supervised learning method. Note that $L_{\text{consistency}}$ and $L_2$ both represent the distance from the neural-network-predicted grasp pose to a certain groundtruth pose, the only difference is that we have only one groundtruth pose in $L_2$ and we have $K$ groundtruth poses in $L_{\text{consistency}}$, so that $L_{\text{consistency}}$ and $L_2$ are comparable.

From the first row of Table II, we can see that, even when simple supervised learning is used at training time, the residual of $L_{\text{consistency}}$ (73.61) is already much smaller than the residual of $L_2$ (2.63). This means that the distance between the neural-network-predicted grasp pose and the closest groundtruth pose is much smaller than the average distance to all the 100 candidate grasp poses. If $L_{\text{consistency}}$ is used as loss function during training time, the residual of $L_{\text{consistency}}$ is further reduced from 2.630 to 0.914. Introducing collision loss does not further reduce residual metrics. However, in the next section, we will see that collision loss will result in grasp poses that are closer to object surfaces, which increases the success rate of grasping.

\[ L_{\text{consistency}} \] and \[ L_2 \] are comparable.

| Loss | Residual | $L_2$ | $L_{\text{consistency}}$ | $L_{\text{combined}}$ ($\beta = 0.75$) |
|------|----------|------|--------------------------|--------------------------------------|
| $L_2$ | 2.630    | 55.865 |                          |                                      |
| $L_{\text{consistency}}$ | 0.914 | 0.261 |                          |                                      |
| $L_{\text{combined}}$ ($\beta = 0.75$) | 0.133 | 0.133 |                          |                                      |

**TABLE II:** We train neural networks using 3 different loss functions (different rows). After training, we summarize the residuals of different loss functions on the test set (different columns). Our consistency loss function drastically reduce the error of neural network in representing a single grasp pose.

3) **Penetration Handling:** Given an object, we first use the neural network to compute a proposed grasp pose. However, this grasp pose can be invalid, with some penetrations into the target object as shown in Figure 9 (a). We can fix this problem by combining two methods. The first method is to introduce collision loss at training time. From Table II, we can see that introducing collision loss does not improve different residuals in general. However, it is very efficient in resolving most penetrations. In our experiment, introducing collision loss leads to an average relative change of learned grasp pose by:

$$\frac{\partial}{\partial x} \sum_{i=1}^{P} \min_{\theta} \left[ f_{\text{collision}}(o_i, \theta) - f_{\text{collision}}(o_1, \theta) \right] = 12.7\%.$$  

When testing the neural network trained without collision loss on the test set, an average of 2.563 of the 45 sample points have penetrations with the target object on average and the penetration depth is 0.0553m. With collision loss, the average number of sample points with penetration is reduced to 0.719 and the average penetration depth is reduced to 0.0081m. However, during runtime, the actual grasping hardware cannot allow any penetrations between the object and the Shadow Hand. A second method is needed to compute a grasp pose without any penetrations, for which we use a simple interpolation method (runtime adjustment). Specifically we compute the gradient of $L_{\text{collision}}$ with respect to the joint angles:

$$\frac{\partial}{\partial x} \sum_{i=1}^{P} \min_{\theta} \left[ f_{\text{collision}}(o_i, \theta) - f_{\text{collision}}(o_1, \theta) \right]$$

and we update our joint pose along the negative gradient direction until there are no penetrations. In practice, a single forward propagation through the neural network takes a computational time of 0.541s and the runtime adjustment takes 0.468s.

4) **Multi-View Depth Image as Input:** To extend our method to real-world scenarios, we evaluate our method on object models with uncertainties or inaccuracies. In our experiment, we select 15 objects from the YCB Benchmarks, none of which is included in our training dataset or test dataset. These 15 objects are captured using a multi-view depth camera and their geometric shapes are constructed using the standard pipeline implemented in [29] and illustrated in Figure 8. Specifically, RANSAC is first used to remove planar background of the obtained point cloud, Euclidean cluster extraction algorithm is then used to find a set of segmented object point clouds, and finally segmented object meshes are extracted using Poisson surface reconstruction. The reconstructed meshes are finally voxelized to a 3D occupancy grid. After pre-process, reconstructed mesh is fed to our neural networks to generate grasp poses. Sometimes, the generated grasp poses are of low quality in terms of the $\epsilon$-metric, in which case we rotate the object mesh and run our neural networks again to generate a new grasp pose. On average, we rotate the object 3-5 times and report the best grasp pose quality in the wrench space. Although these...
reconstructed object meshes have noisy surfaces, we still get an average grasp quality of 0.102, over the 15 objects, where we use the $\epsilon$-metric to measure grasp quality. Some grasp poses are shown in Figure 10.

**5) Comparison with Prior Methods:** The main different between our method and prior works [9], [34], [6] is that we target at high-DOF grasp poses and we use a neural network to directly generate grasp poses, instead of the score of a candidate grasp pose. Our method still needs a sampling-based algorithm to randomly rotate the target object and pick the best grasp. However, unlike [9] that requires hundreds of samples, our method only needs 3-5 samples, which can be computed within 3-5 seconds. On the other hand, a major drawback of our method is that we require a very large dataset, with tens of grasp poses for each target object. We find this dataset an essential component to make our method robust when generating grasp poses for unseen objects, as shown in Figure 12. Most of the generated grasp poses are of similar quality as groundtruth poses generated from GraspIt! as shown in Figure 11.

**VI. Conclusion and Limitation**

We present a new neural-network architecture and a training technique for the generation of high-DOF grasp poses. To resolve the grasp pose redundancy, we use a consistency loss and let the neural network pick the best or most-representable grasp poses for each target object. To further improve the quality of grasp poses, we introduce a collision loss to...
resolves penetrations between the hand and the object. Our results show that conventional supervised learning will not result in accurate grasp poses while a neural network trained using our consistency loss drastically improves the accuracy of grasp poses, compared to the groundtruth. Further, the collision loss can effectively resolve penetrations between the gripper and the target object, on both the training set and the test set.

A major limitation of our current method is that it requires a very large dataset containing many effective grasp poses for each target object. This is essential for the neural network to select consistent grasp poses. However, when we have a very large set of target objects, generating such a dataset can be very computationally costly and lots of computations can be wasted because the computed grasp poses are not selected by the neural network.

There are several avenues for future work. One is to consider an end-to-end architecture that predicts grasp poses directly from multi-view depth images, similar to [34]. Another direction is to consider more topologically complex target objects, such as high-genus models. In these cases, a signed distance representation is not enough to resolve the geometric details of objects and the collision loss needs to be reformulated. Finally, our current method has been evaluated on a single high-DOF gripper model, the Shadow Hand, and it is useful to generalize the ability of the neural network to represent grasp poses for other high-DOF gripper models such as a humanoid hand model.

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