

Robust Grasp Planning Over Uncertain Shape Completions

Jens Lundell, Francesco Verdoja and Ville Kyrki

Abstract—We present a method for planning robust grasps over uncertain shape completed objects. For shape completion, a deep neural network is trained to take a partial view of the object as input and outputs the completed shape as a voxel grid. The key part of the network is dropout layers which are enabled not only during training but also at run-time to generate a set of shape samples representing the shape uncertainty through Monte Carlo sampling. Given the set of shape completed objects, we generate grasp candidates on the mean object shape but evaluate them based on their joint performance in terms of analytical grasp metrics on all the shape candidates. We experimentally validate and benchmark our method against another state-of-the-art method with a *Barrett hand* on 90000 grasps in simulation and 200 grasps on a real *Franka Emika Panda*. All experimental results show statistically significant improvements both in terms of grasp quality metrics and grasp success rate, demonstrating that planning shape-uncertainty-aware grasps brings significant advantages over solely planning on a single shape estimate, especially when dealing with complex or unknown objects.

I. INTRODUCTION

In robotic grasping, knowing the object shape allows for better grasp planning. However, in many environments it is impossible to know a priori the shape of all possible objects. For this reason, the object to be grasped is usually perceived through some sensory input, commonly vision. However, one of the main problems with this approach is that only one side of the object is perceived, due to object self-occluding its back side. To cope with this limitation, essentially two options exist: (i) use the information perceived and generate grasps based on this knowledge alone [1], [2], or (ii) from the same input extract additional knowledge of the object with, for example, semantic segmentation [3] or shape completion [4], [5] and plan grasps accordingly.

In this paper, we focus on the latter, that is shape completion, and train a deep network to estimate the complete object shape. However, in contrast to most recent work in the field [6]–[8] where the focus is explicitly on generating more exact point estimates of the shape, this work takes another viewpoint of the problem by also modeling the uncertainty over the completed shape. This uncertainty can then be incorporated into probabilistic grasp planners to enable robust grasp planning over uncertain shapes.

To this end, we propose a Deep Neural Network (DNN) architecture with dropout layers active both during training and testing (Section III-B). With such a structure, uncertainty

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Fig. 1: The real world setup with the *Franka Emika Panda* robot and the 10 objects used in the experiments.

is quantified from the difference in samples generated from feeding the same input through the network multiple times but each time with a different dropout mask. This use of dropout was originally proposed in [9] as a method for approximate Bayesian inference in deep Gaussian processes.

Another open issue is how to plan grasps over uncertain shapes. We address this by incorporating the uncertainty into probabilistic grasp planning (Section III-A) and propose a computationally tractable method for planning robust grasps over uncertain shapes (Section III-C). The proposed method is experimentally validated (Section IV) by comparing it to a deep learning-based method [4] that only generates a point estimate of the shape in terms of shape reconstruction (Section IV-B), analytical grasp quality metrics in simulation (Section IV-C), and grasp success rate on the real *Franka Emika Panda* seen in Figure 1 (Section IV-D). Simulations of 90000 grasps demonstrate a statistically significant improvement in recognizing grasps with high quality metrics when including the shape uncertainty. The physical experiments of 200 grasps also show statistically significant improvement in terms of higher grasp success rate when planning is performed over the shape distribution compared to solely planning on a point estimate of the shape.

The main contributions of this work are: (i) a novel shape completion DNN architecture able to capture shape uncertainties, (ii) a probabilistic grasp planning method that utilizes the shape uncertainty to propose robust grasps, and (iii) an empirical evaluation of the proposed method against state-of-the-art, presenting, both in simulation and on real hardware, a statistically significant improvement using the proposed method both in terms of grasp ranking and on grasp success rate.

II. RELATED WORKS

A. Probabilistic Grasp Planning

Probabilistic grasp planning addresses the issue of planning grasps under uncertainty. Typical uncertainties in robotic grasping are related to object pose uncertainty [10]–[12], object shape uncertainty [5], [13], [14], or friction and contact position uncertainty [15].

For instance, Hsiao *et al.* [10] developed a Bayesian framework to generate grasps that were robust to both pose and shape uncertainty as well as robot motion error by simulating grasps on deterministic mesh and point cloud models. A similar framework was also used in [11], where they use Gaussian Processes (GP) to model the grasp stability from tactile feedback and Markov Chain Monte Carlo (MCMC) to propose stable grasps.

In terms of grasping under shape uncertainty, Li *et al.* [13] proposed a method that models the shape uncertainty with a GP, encodes it as a grasp planning constraint, and optimizes for a grasp that minimizes the distance between the center of the contact points and the origin of the object. They then cast the problem of computing a hand configuration that can realize the grasping location as a learning problem. However, the shape reconstruction performance of that method is conditioned on possibility to sample any subset of point of a complete point-cloud of the object. This limitations makes it difficult to apply on unknown objects, something we address in this work.

Mahler *et al.* [5] instead use Gaussian Process Implicit Surfaces (GPISSs) to represent shape uncertainty and measures grasp quality by the probability of force closure. Tangential to the works using GP to model shape uncertainty is the work in [14], where they use probabilistic Signed Distance Function (p-SDF) to represent shape uncertainty and a simulated annealing approach to search and optimize grasps. However, [5] only consider shape uncertainty in 2D and [14] requires multiple views of objects for shape reconstruction, whereas our method reasons about the shape uncertainty in 3D from only one viewpoint.

B. Shape Completion

In this work we refer to shape completion methods as shape reconstruction from an incomplete point-cloud. Most such methods fall into one of three distinct categories: 1) Geometric approaches, 2) Template-based approaches, and 3) Deep learning-based approaches. Here, we will mainly focus on the third category and refer to [16] for an in depth survey over the first two.

The first category, geometric approaches, includes symmetry driven [17] and heuristic methods [18]. The former reconstructs a shape by mirroring the input object through its symmetry axis while the latter reconstructs the shape by combining primitives such as planes and cylinders into one final shape. Template-based approaches, on the other hand, seek to match the input to an object in a database and then deform it to match the input [19]. Although many of these approaches originates from the computer vision perspective

where the focus is on achieving better shape reconstruction, similar work have also been successfully applied in robotics. For example to facilitate robotic grasping by using symmetry [20], heuristics [21], or template matching methods [22]. However, these methods are only applicable for specific sets of objects. For example, mirroring fails if the object has more than one axis of symmetry, whereas heuristics and template based matching are computationally restricted to specific subset of objects. Our method, on the other hand, do not rely on either symmetry or a known set of objects and is therefore more general.

More modern shape completion methods are based upon deep learning [4], [6]–[8], [23]. In this context, most recent improvements originate from more refined network structures [6], [8], from the inclusion of semantic object classification [7], or from incorporating other sensing modalities such as tactile information [23].

In terms of similar methods applied to robotics, only two works exist [4] and [23]. Both of these work used shape completion to facilitate robotic grasping where the latter one extended the former by incorporating tactile information of the object to improve shape reconstruction. In [4] the authors propose an hourglass Convolutional Neural Network (CNN) architecture to reconstruct the shape given a voxel grid of the input point-cloud. That architecture, however, employs fully connected up-sampling layers resulting in a network with approximately 300 million parameters. Our network, on the other hand, has approximately 10 times less parameters as it uses convolutional layers throughout.

Together, all deep learning-based shape completion methods have solely focused on improving quality of the object shape estimate. This work, on the other hand, shifts the focus from single point estimates and explores estimation of the shape uncertainty. This is especially valuable in robotic grasping as it allows planning grasps that are robust to shape uncertainty.

III. METHOD

A. Probabilistic Grasp Planning

Let us define G as the set of all possible grasps, represented as 6D end-effector pose and joint values, obtained by a grasp planning strategy. Traditional grasp planning can be formalized in a probabilistic framework as an attempt at generating a candidate grasp $g \in G$ whose stability S is maximized over a perfectly known object shape o . Formally,

$$\arg \max_{g \in G} P(S | g, o) , \quad (1)$$

where $P(S | g, o)$ is usually estimated by using some defined grasp quality metric such as the epsilon- (ϵ -) or volume-measure (v -measure) [24].

In this work we follow the same procedure of maximizing a grasp quality metric but do not assume perfect knowledge of the object shape. Instead, the shape is modeled as a probability distribution $P(O | r)$ conditioned on some measurements r representing, for example, a partial view

of the object in the form of a point-cloud. Consequently, we have that

$$P(S | G, r) = \int P(S | G, O)P(O | r) dO . \quad (2)$$

The marginalization over shapes O in (2) is intractable beyond the simplest cases where we only target a specific class of objects [10]. To circumvent this problem, we propose using a sampling scheme to approximate (2)

$$P(S | G, r) \approx \frac{1}{N} \sum_{i=1}^N P(S | G, o_i) , \quad (3)$$

where $o_i \sim P(O | r)$. The actual sampling process $o_i \sim P(O | r)$ is described in Section III-B.

Maximizing (3) requires a set of grasps candidates $g \in G$. However, generating those on all shapes o_i is computationally infeasible. For that reason, instead of planning separate grasps on each shape o_i , we compute a mean shape $\hat{o} = \mathbb{E}[o_i]$ and only sample grasps on that, obtaining a set of candidate grasps $\hat{G} \subseteq G$. Finally, each grasp candidate in \hat{G} is evaluated on all samples o_i and the one with the highest average grasp quality metric across all samples is considered most robust. Formally, the most robust grasp solves

$$\arg \max_{g \in G} P(S | g, r) \approx \arg \max_{\hat{g} \in \hat{G}} \frac{1}{N} \sum_{i=1}^N P(S | \hat{g}, o_i) . \quad (4)$$

B. Sampling Based Shape Completion

One of the crucial parts of the framework presented in Section III-A is the sampling process we employ to estimate the posterior distribution $P(O | r)$, *i.e.*, how to obtain a distribution of shapes from a partial sensor reading. One option is to use a Bayesian Neural Network (BNN), but for most forms of neural networks, such as the one used in this work, computing the full posterior is computationally intractable [25]. Therefore, we propose to approximate $P(O | r)$ using variational inference through the use of dropout sampling [9], where samples generated by having the dropout layers active also during test-time and feeding the same input through the network multiple times are used to approximate the full posterior $P(O | r)$. This procedure, known as Monte-Carlo (MC)-Dropout, is a method to achieve approximate inference in Gaussian processes and DNNs [9].

To enable using MC-Dropout, and in turn estimate $P(O | r)$, we propose to use the DNN \mathcal{H} shown in Figure 2 to generate a shape o given a sensor reading r , that is $o = \mathcal{H}(r)$. The network architecture is inspired from [26] but with a few important modifications to tailor it to our application: the input data dimensions (*i.e.*, voxel size) is changed (40^3 compared to 32^3), to have fewer layers, and most importantly seven dropout layers [27] are included. The network is trained in a supervised fashion with the cross-entropy error [4]

$$E(o, \tilde{o}) = -(o \log(\tilde{o}) + (1 - o) \log(1 - \tilde{o})),$$

where o is the network output and \tilde{o} is the ground-truth target.

Shape samples $o_i \sim P(O | r)$ for one measurement r are then generated with MC-Dropout. The results is a set $O_{\mathcal{I}} = \{o_i\}_{i=1}^N$ of shapes. Given this set, we then evaluate the mean shape \hat{o} and use it to generate the subset of grasps candidates \hat{G} as mentioned in Section III-A.

C. Robust Grasp Planning Over Uncertain Shapes

We propose Algorithm 1 to plan robust grasps over uncertain shapes. In short, the algorithm first create a number of sample shapes based on an observation (lines 7-13), then plans a set of candidate grasps on the mean shape (line 16), and finally evaluate each of the grasp candidates on the entire set of shapes (lines 17-24).

To generate the shape candidates, the algorithm first voxelizes the input point-cloud (line 6). Then, I samples are generated by following the procedure detailed in Section III-B. To transform a voxel grid the network outputs into a mesh we used the algorithm SHAPE COMPLETION proposed in [4].

The mean object mesh is created by first averaging all voxel grids into a mean voxel grid (line 14) and then transforming it into a mesh (line 15). Grasps are then planned on the mean mesh (line 16) and a procedure to do this is described in Section IV-A.

Next, each grasp is separately evaluated on every sample (line 20). Finally, given the grasp quality metrics on all samples, grasps are ranked (line 25) by first averaging the quality metric of each grasp across all samples and then rank the grasps according to the new average quality metric, where the highest ranked grasp corresponds to highest average quality metric. It follows that the highest ranked grasp is also the solution to (4) which, in this work, is considered the most robust grasp over the shape uncertainty.

IV. EXPERIMENTS

The two main questions we wanted to answer in the experiments were:

- 1) What is the shape reconstruction accuracy of the proposed method?
- 2) What is the impact of estimating shape distributions on grasp quality and grasp success rate?

In order to provide justified answers to these questions we conducted three separate experiments. The first experiment (Section IV-B) examines general shape reconstruction accuracy, the second one (Section IV-C) evaluates grasp quality metrics in simulation, while the third experiment (Section IV-D) evaluates grasp success rate on real hardware. In the first two experiments we compare our method with dropout sampling, ours without dropout sampling¹, and Varley’s method [4] which is the only shape completion method proposed for grasping. In the third experiment we only compare our method with dropout sampling to Varley’s. Henceforth, we refer to the three methods as Uncertain Shape Network (USN), Shape Network (SN), and Varley (V) respectively.

¹by without dropout sampling we mean that dropout layers were enabled during training, but then disabled at test-time.

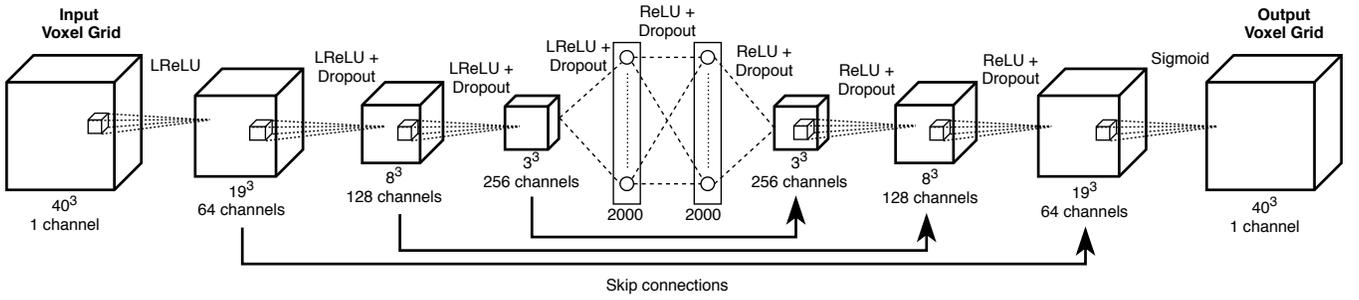


Fig. 2: The proposed network architecture. In this architecture, ReLU stands for rectified linear unit and LReLU for leaky rectified linear unit.

Algorithm 1 Robust Grasp Planning Over Uncertain Shape

- 1: **Inputs:** Point-cloud \mathbf{P} and number of dropout samples I
 - 2: Initialize empty object voxel set $O_I \leftarrow \{\}$,
 - 3: Initialize empty object mesh set $O_M \leftarrow \{\}$,
 - 4: Initialize empty grasp sets $G, \hat{G} \leftarrow \{\}$,
 - 5: Initialize empty grasp quality metric set $S \leftarrow \{\}$
 - 6: $\mathbf{P}_V \leftarrow \text{VOXELIZE}(\mathbf{P})$
 - 7: **for all** $i = 1, \dots, I$ **do**
 - 8: Sample dropout mask B
 - 9: $o_i \leftarrow \mathcal{H}_B(\mathbf{P}_V)$
 - 10: $o_m \leftarrow \text{SHAPECOMPLETION}(o_i, \mathbf{P})$
 - 11: $O_I \leftarrow O_I + \{o_i\}$
 - 12: $O_M \leftarrow O_M + \{o_m\}$
 - 13: **end for**
 - 14: $\hat{O} \leftarrow \text{E}[O_I]$
 - 15: $\hat{O} \leftarrow \text{SHAPECOMPLETION}(\hat{O}, \mathbf{P})$
 - 16: $\hat{G} \leftarrow \text{PLANGRASP}(\hat{O})$
 - 17: **for all** $\hat{g} \in \hat{G}$ **do**
 - 18: $S_g \leftarrow \{\}$
 - 19: **for all** $o_m \in O_M$ **do**
 - 20: $s \leftarrow \text{EVALUATEGRASP}(\hat{g}, o_m)$
 - 21: $S_g \leftarrow S_g + \{s\}$
 - 22: **end for**
 - 23: $S \leftarrow S + \{S_g\}$
 - 24: **end for**
 - 25: $G \leftarrow \text{RANKGRASPS}(\hat{G}, S)$
 - 26: **return** G
-

A. Experimental Setup

For training and testing the network proposed in Section III-B we used the same data as in [4], that is voxelized occupancy grids of objects from the YCB and Grasp Database. The test-data consisted of two separate sets, holdout views and holdout model: the former is novel views of the objects used for training, while the latter are completely novel objects. The network itself was implemented in PyTorch 0.3.0 with a dropout rate of 0.2, and trained with Adaptive Moment Estimation (Adam) [28] using a batch size of 32 and for 181 epochs². The training was carried out on an

²Code available at: irobotics.aalto.fi/software-and-data/shape-completion

NVIDIA Titan Xp and lasted for approximately a week. For evaluating V we used a pre-trained network made publicly available by the authors³.

In the first two experiments we generated test data with the same procedure as in [4], that is randomly sampling 50 views from the training set (*Training Views*), 50 views from the holdout view set (*Holdout Views*), and 50 views from the holdout models set (*Holdout Models*). In the real world experiments the methods were evaluated on the 10 objects shown in Figure 3.

We used GraspIt! [29] to generate grasp candidates in both the simulated and real world grasping experiments. As our method is agnostic to the type of quality metric, in simulation we decided to evaluate two different ones: ϵ - and the v -measure [24] as the former represents the quality metric of a worst case grasp and the latter an average case grasp. More specifically, the ϵ -measure represents the radius of the largest 6D ball centered at the origin that can be enclosed by the convex hull of the wrench space, while the v -measure represents the volume of that convex hull. On the real hardware, however, only the ϵ -measure was used as it attained a higher grasp success rate for both methods, according to a small pilot.

B. General Completion Results

To evaluate the general shape completion results we use the Jaccard similarity, which is defined as

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}. \quad (5)$$

where A and B are two sets. In this work A is the ground truth and B is the shape reconstructed with shape completion. In order to generate the sets A and B we follow the same procedure as in [4], that is to voxelize each mesh to a resolution of 40^3 .

To quantify the reconstruction results for USN we generated 10 dropout samples and evaluated the Jaccard similarity on the mean mesh. The shape reconstruction results for V, SN, and USN are presented in Table I. We can see that there is essentially no difference between the three methods, meaning that our network—with and without dropout enabled at

³shapecompletiongrasping.cs.columbia.edu

TABLE I: Jaccard similarity results (higher is better)

View	V	SN	USN
Training Views	0.6205	0.6480	0.6446
Holdout Views	0.6143	0.6382	0.6389
Holdout Models	0.5632	0.5573	0.5651

test-time—scored equally well as Varley’s, a network that is approximately 10 times larger than ours. Moreover, the results do indicate that the mean shape approximated by averaging shape samples is representative for the mean of the unknown underlying shape distribution.

It is worth pointing out that the presented Jaccard similarity are substantially lower than the ones reported in [4] where V achieves a reported score of 0.7771, 0.7486, and 0.6496, on training views, holdout views, and holdout models respectively. One reason for not attaining similar scores here is that we do not know the exact objects they included in the different test sets. Instead, we had to sample new ones and because of that some object that were in the test sets in [4] were most likely not in the test sets here and vice versa.

C. Grasping in Simulation

In the simulated grasping experiment we evaluated the methods’ capability at recognizing good grasp candidates. We evaluated 600 grasps for each of the 150 shape completed objects in the test sets. To quantitatively compare grasps between methods, grasp directions were uniformly sampled around the object using GraspIt!. Then the two separate grasps for each method, one achieving the highest ϵ -measures and the other the highest v -measures, were evaluated on the ground truth object.

For the last step we followed the same strategy as in [4], that is to swap the shape completed object for the ground truth in GraspIt!, place the hand 20cm backward along the grasp approach vector, set the spread of its fingers, move it along the grasp approach vector until the pose was reached, and finally close the fingers.

The methods compared were V, SN, and USN. USN was evaluated on 10 dropout samples using the grasp planning method detailed in Section III-C. The other methods chose the grasps according to their performance on the point estimate of the shape.

To analyze the statistical differences between the methods we used a one sided Wilcoxon signed-rank test; the results are presented in Table II. Based on these results we can draw several interesting conclusions. For once, there is a statistical significant improvement using USN over V for determining the most robust grasp in terms of both ϵ - and v -measure. A similar statistical significant improvement was also visible for USN over SN but only in terms of v -measure. The reason for USN outperforming both V and SN is that the performance of these methods deteriorates heavily in the shift from training or holdout views to holdout models, indicating that they are not able to recognize high quality grasps on novel objects. For instance, the relative performance drop



Fig. 3: The 10 different objects with their corresponding number. All objects except number 7 are from the YCB object set.

for V and SN from training views to holdout models are -51.5% and -60% for ϵ -measures and -54.1% and -16.7% for v -measures, respectively. On the other hand USN loses only -4.5% for ϵ -measure and gains +21% for v -measures, that is USN actually performs better on novel objects in terms of the v -measure. These results demonstrate the importance of including shape uncertainty in grasp planning especially in cases where the uncertainty is higher, such as with novel objects.

D. Grasping on Real Hardware

As a final experiment we compared USN with 20 dropout samples and V in terms of grasp success rate on real hardware. To this end, we used a *Barrett hand* mounted on a *Franka Emika Panda* to grasp the 10 different objects visualized in Figure 3. Out of these objects 1, 2, 4, 5, 7, and 10 have one axis of symmetry; 3, 6 and 9 have two; and 8 has three.

We ran the complete grasping pipeline for each object in five different orientations (0° , 72° , 144° , 216° , and 288°) and from two different camera viewpoints: one looking at the object from the left side of the robot and the other from the opposite side of the object to the robot. In total this setup amounts to 100 grasps per method. GraspIt!’s simulated annealing planner [30] was used to plan and evaluate grasps as this sped up the process of planning and evaluating grasps compared to the uniform planning process used in Section IV-C.

To evaluate if a grasp was force-closure, the robot moved to the planned grasp pose, then closed the hand and moved the arm upward 20cm, then moved back to the starting position and finally rotated the hand $\pm 90^\circ$ around the last joint. If the object was stable in the hand for this whole procedure we deemed it force-closure. If the robot, on the other hand, was not able to grasp the object or the object moved inside the hand during the arm motion we deemed it not force-closure.

The experimental results are shown in Table III, where we report the percentage of successful grasp attempts (*Grasp Success Rate*), the average time a method required to complete a mesh from a partial view (*Shape Completion Time*), and the average time the planner required to plan and evaluate individual grasps (*Grasp Evaluation Time*). To analyze the statistical differences between the methods in terms of grasp success rate we used a one sided Wilcoxon signed-rank

TABLE II: Average ϵ and v -quality metrics over different test sets, with test statistics and p -values of pair-wise one sided Wilcoxon signed-rank test for V vs. USN and SN vs. USN. USN was evaluated on 10 dropout samples.

	V		SN		USN		V vs USN		SN vs USN	
	ϵ	v	ϵ	v	ϵ	v	ϵ	v	ϵ	v
Training Views	0.0594	0.1212	0.0757	0.1674	0.0682	0.1976	–	–	–	–
Holdout Views	0.0614	0.1504	0.0590	0.1297	0.0584	0.2127	–	–	–	–
Holdout Models	0.0288	0.0556	0.0300	0.1394	0.0651	0.2404	T=102, p<.001***	T=42, p<.001***	T=167.5, p<.01**	–

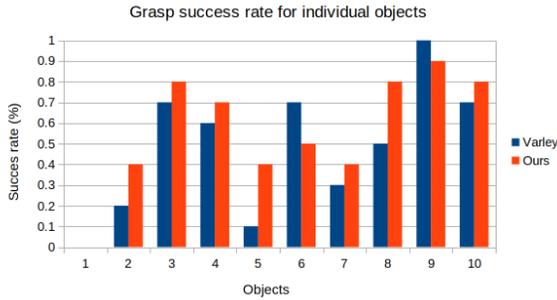


Fig. 4: The individual grasp success rate for both methods on each of the 10 objects used in the experiment.

TABLE III: Real Hardware experiment results. USN was evaluated on 20 dropout samples.

	V	USN
Grasp Success Rate (%)	48	59
Shape Completion Time (s)	7.4	86.73
Grasp Evaluation Time (s)	16.53	83.25

test. The test showed a statistical significant improvement ($T=203.5$, $p<.05^*$) on grasp success rate of USN over V. Furthermore, Figure 4 shows that the grasping performance on individual shapes varies a lot between methods. For example, no method managed to generate a stable grasp for object 1 (the toy airplane) due to its low frictional surface. If we do not consider object 1, our method was more robust on grasping objects with only one axis of symmetry (objects 2, 5, 7 and 10), whereas for the objects with more axis of symmetry V and USN were better on two objects each, observations that may result from random effects. Together, based on the above results, it stem to reason that including shape uncertainty when planning grasps compared to only planning on a point estimate of the shape improves grasps success rate especially on complex objects which are more difficult to complete.

Again, as was noted in Section IV-B, we did not achieve similar results for V as reported in [4] where the grasp success rate was 93.33%. This difference is most likely due to the fact that we perform many more grasps (100 compared to 15) and use fewer easy-to-complete shapes such as boxes (1 compared to 4) and instead included harder objects, *e.g.*, the metallic cup (see Figure 5).

In Figure 5 we show one shape completion example. It

is clearly visible that from the point-cloud in Figure 5b the shape completed object using V (Figure 5c) severely underestimates the thickness of the object and is unable to connect the handle to the body of the cup. In contrast the mean object shape using USN (Figure 5d), although still far from perfect, is definitely better at estimating the real thickness of the cup and is also able to connect the handle to it. Three of the twenty samples used to create the mean mesh are visualized in Figures 5e-5g and individually they show very interesting behaviors. For example, the object shown in Figure 5e is very thick and completely fills the cup while the one in Figure 5f is rather thin in the bottom half. The object in Figure 5g, on the other hand, models the overall shape well but is instead irregular. Viewed together, the samples are consistent in areas covered by the point-cloud, which is expected as the confidence there is high, while more uncertain in areas that are occluded to the point-cloud. As the different samples capture different possible shape completed object, planning grasps that are good on all samples makes the grasps more robust to shape uncertainty.

Although our method achieved a higher grasp success rate it also requires longer computational time as seen in Table III. It is, however, possible to substantially lower both the completion and evaluation time by harnessing the inherent parallel structure of Algorithm 1. For instance, to lower evaluation time all grasps could be evaluated in parallel on each of the object samples. Similarly, the shape completion time could be lowered by doing shape sampling in parallel through multiple copies of the USN network with individual dropout masks.

V. CONCLUSIONS

We presented a method for generating robust grasps over uncertain shape completions. The key insight was to use dropout layers not only during training but also at run-time to generate shape samples and then rank grasps based on their joint quality metrics over all the samples. We compared our method to current state-of-the-art shape completion methods used in robotics both in simulation and on real hardware. Together all results from shape reconstruction, simulation, and real hardware indicated that including shape uncertainty did lead to statistical significant improvements in terms of recognizing good grasps and achieving higher grasp success rate while keeping shape reconstruction quality comparable to the benchmark.

In conclusion the work presented here demonstrates that

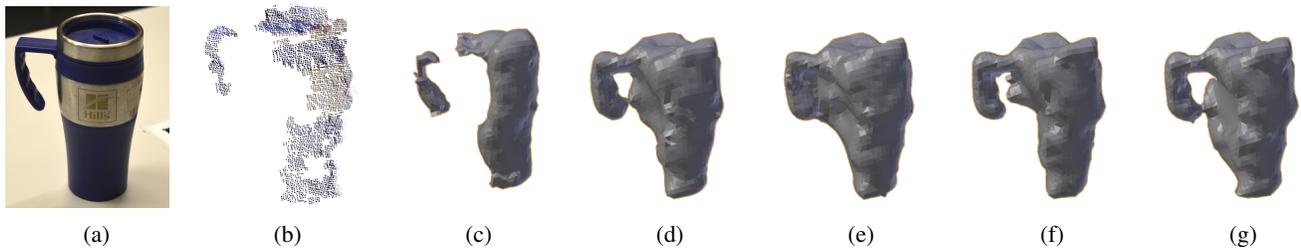


Fig. 5: (a) shows the real object and a point-cloud of it is visible in (b). Given this point-cloud, (c) shows the shape completed object using V and (d) the mean shape completed object using USN. Three of the in total twenty samples used to generate (d) are shown in (e)-(g).

planning shape-uncertainty-aware grasps brings significant advantages over solely planning on a good point estimate. This, in turn, poses new interesting research questions. For instance, can more refined shape completion networks [6], [8] benefit from modeling uncertainty? Similarly, from a robotics perspective, can the performance of end-to-end methods such as Dex-Net [1] improve if they also included uncertainty as a part of the network? These questions pave the way for interesting future research avenues.

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