Improved GQ-CNN: Deep Learning Model for Planning Robust Grasps

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1 Abstract
Recent developments in the field of robot grasping have shown great improvements in the grasp success rates when dealing with unknown objects. In this work we improve on one of the most promising approaches, the Grasp Quality Convolutional Neural Network (GQ-CNN) trained on the DexNet 2.0 dataset [15]. We propose a new architecture for the GQ-CNN and describe practical improvements that increase the model validation accuracy from 92.2% to 95.8% and from 85.9% to 88.0% on respectively image-wise and object-wise training and validation splits.

2 Background
Robot grasping. Robot grasping is one of the most important tasks on the way to a wide adoption of robots at our homes and in the industry. However, grasping is also one of the most challenging tasks to solve.

Robot grasping methods can be categorized based on the type of grasp success criteria as either analytical [19, 18, 21] or empirical (data-driven) [1]. In analytical methods, physics simulations are used to precompute the grasp robustness scores based on predefined 3D models and the most robust grasp for the best matching 3D model is executed [2, 5, 9, 14]. In empirical methods, the grasp success is predicted directly from the robot sensors, typically using machine learning models [1, 13]. The empirical methods are usually a lot faster and generalize better to variations in object shapes and to unseen objects than the analytical methods. However, the empirical methods often require a large number of labels to train. Such labels can be either obtained from tedious human labeling [3, 8, 12, 6, 20] or long running physical trials [17, 16, 13].

Grasp Quality CNN The work by Mahler et al. [15] that forms the basis for our work is an empirical method for robot grasping. They train a CNN on a large dataset of physics-based generated labels to predict the grasp success. More precisely, they generate a Dex-Net 2.0 dataset that contains 6.7 million point clouds and analytical grasp success metrics for parallel-jaw grasps based on a dataset of 1,500 3D object models. They devise a Grasp Quality CNN (GQ-CNN) network for predicting the grasp success based on the 2.5D point clouds from a depth camera. Finally, they develop a grasp planning policy that samples grasps and ranks them using the trained GQ-CNN. Their solution provides very promising results that is comparable in grasp success with the state-of-the-art analytical methods, but outperforms them for unseen objects and is 3× faster.

3 GQ-CNN improvements
Encouraged by the success of the original work by Mahler et al. [15] we propose improvements to their GQ-CNN network. Our improvements come in two forms. First, we propose a new CNN architecture that achieves higher test accuracy on synthetic data. Second, we improve their data augmentation procedure, which results in an increased robustness of the model.
3.1 Problem statement

We are interested in planning a robust planar parallel-jaw grasp of a single object on a table from a 2.5D point cloud. GQ-CNN learns a function that takes as input $32 \times 32$ depth images and a grasp depth $z \in \mathbb{R}$ and returns the grasp success probability. The planar position of the grasp is defined by the center of the input image and the orientation of the gripper $\varphi$ is parallel to the horizontal axis of the image.

3.2 New GQ-CNN architecture

The main contribution of this paper is the new architecture for the GQ-CNN (see Figure 1). We highlight the key discrepancies between our architecture and the original GQ-CNN architecture. First, instead of merging the image and the grasp depth towers using a fully connected layer, we combine the two with a convolutional layer. To achieve that we reshape the grasp depth value $z$ to match the 2D shape of the corresponding convolution layer in the tower for the image input. The convolutional layer, as opposed to the fully connected layer, persists the spatial information even after the depth of the grasp is known. We also add two additional convolutional layers after the two towers are merged. We hypothesize that this allows the model to focus its attention on the spatial locations with heights similar to the grasp height. Furthermore, we increase the number of filters and add an additional max pooling operation after the last convolutional layer in the image tower. This results in a deeper and more complex network architecture than the original one. Finally, instead of using the Local Response Normalization (LRN) \cite{11} after the second and fourth convolutional layer, we employ Batch Normalization \cite{7} after each of the convolutional layers.

3.3 Data augmentation

Our second contribution is the analysis and improvement of the data augmentation procedure. In particular, we investigate the impact of the data augmentation on the test accuracy of the model (on synthetic data). Below we describe the augmentations from the original work (symmetrization, multiplicative aug. and Gaussian Process aug.) and propose a modification to the multiplicative augmentation where we additionally adjust the grasp depth $z$. Separately from the below augmentations, all the input images are normalized by subtracting their pixel mean and dividing by their standard deviation (‘Normalize’).

**Symmetrize** Images are flipped vertically or horizontally with 50% probability.

**Multiplicative augmentation** All pixels in an image are multiplied by a random variable from a univariate Gamma distribution:

$$f(x, a, b) = \frac{x^{a-1}e^{-\frac{x}{b}}}{b^a\gamma(a)}$$

where shape $a = 1000$ and scale $b = \frac{1}{\sigma} = 0.001$. This results in multiplying the image by a random noise highly concentrated around $\mu = 1$ ($\sigma = 0.0316$).

**Gaussian Process augmentation** An additive augmentation applied with 50% probability, where a Gaussian Process (GP) noise is added to the pixel values. The GP noise is simulated by generating a matrix of size $8 \times 8$ with values from a univariate Gaussian with $\mu = 0$ and $\sigma = 0.005$ and upsampled using bicubic interpolation.

Figure 1: Our GQ-CNN architecture.
Multiplicative augmentation with grasp depth \( z \) adjustment  While the above multiplicative augmentation effectively changes the height of the scene in the image, it neither adjusts accordingly the grasp depth nor does it change the label grasp quality. Therefore, we propose to adjust the grasping height by the exact same multiplicative augmentation as done to the pixels so that we obtain a new example with a correct label as calculated for the image before the augmentation.

4 Experiments

4.1 Experimental setup

We perform our experiments on the same dataset training/validation splits as used in [15]. In particular, we report our results on three different splits of training and validation datasets:

- Object split: based on the unique objects (same object cannot be present in training and validation).
- Pose split: based on the unique poses of objects (same object can be present in both training and validation).
- Image split: based on the unique grasps (poses and objects can mix between the training and validation dataset).

In the experiments we use our GQ-CNN architecture as described in subsection 3.2. Optimization is performed using an Adam optimizer [10] with learning rate \( 10^{-4} \) and an exponential decay rate of 0.95 every 50000 steps, a weight decay of \( 10^{-5} \) and a batch size of 128.

4.2 Improved GQ-CNN results

Table 1 compares the results of our version of the GQ-CNN with the version from Mahler et al. [15]. Our GQ-CNN network outperforms the baseline in the image split and achieves comparable results on the pose and object splits. We attribute the improvement on the image split to the higher expressiveness of our GQ-CNN (larger number of weights), which results in a better fit to the training data (see ‘Normalize’ in Figure 2). In the image split, the training data is very similar to the test data and thus our GQ-CNN achieves much better performance also on the validation data.

| Train/validation split type | Image | Pose | Object |
|-----------------------------|-------|------|--------|
| Mahler et al. [15]          | 92.2  | 88.9 | 85.9   |
| Ours (no data aug.)         | 96.7  | 88.2 | 86.7   |

Table 1: Validation accuracy of the GQ-CNN on different types of splits.

4.3 Data augmentation results

We investigate the impact of the data augmentation on the model performance and generalization, but also on the calibration of its predictions.

4.3.1 Analysis of the data augmentation

We analyze the impact of different augmentation procedures described in subsection 3.3. Table 2 and Figure 2 show the obtained validation accuracies for different combinations of the augmentations when tested on the image split. We observe that adding the additional augmentations reduces the validation accuracy on the image split, but also decreases the over-fit to the training data. The results also show that our proposed adjustment of the input depth variable \( z \) along with the pixel values during multiplicative augmentation improves the model performance.

| Normalize | Symmetrize | Mult. Aug Pixels | Mult. Aug. Z (ours) | GP. Aug | Val. Acc |
|-----------|------------|------------------|---------------------|---------|----------|
| ✓         | ✓          | ✓                | ✓                   | ✓       | 96.78    |
| ✓         | ✓          | ✓                | ✓                   | ✓       | 94.64    |
| ✓         | ✓          | ✓                | ✓                   | ✓       | 96.03    |
| ✓         | ✓          | ✓                | ✓                   | ✓       | 95.75    |

Table 2: Impact of different data augmentations on the validation accuracy on the image split.

\(^1\)The result for the image splits was also replicated by the authors of the original GQ-CNN model [15] and can be found on their leaderboard. See: https://berkeleyautomation.github.io/gqcnn/benchmarks/benchmarks.html
4.3.2 Impact on generalization

To verify that the additional data augmentations improve the generalization, we compare the model with and without
the augmentations on all the three splits. Table 3 shows that the augmentations in fact increase the validation
accuracy on both the pose and the object split, while maintaining the high image split performance. This indicates
that the data augmentations result in an increased generalization of the model.

| Train/validation split type | Image | Pose | Object |
|----------------------------|-------|------|--------|
| Mahler et. al              | 92.2  | 88.9 | 85.9   |
| Our GQ-CNN no aug.         | 96.7  | 88.2 | 86.7   |
| Our GQ-CNN all aug.        | 95.8  | 89.7 | 88.0   |

Table 3: Validation accuracy on the different types of splits.

4.3.3 Calibration

Calibration indicates the relation between the predicted probability of success vs ground-truth success proportion.
The ground-truth success proportion is calculated as the mean of success metric for predictions within a bucket with
predictions within a given success probability range. For instance, predictions in a bucket with success probability
between 55% and 65% with perfect calibration would have a ground-truth mean success proportion of around 60%.

An accurate calibration of the prediction probabilities is crucial in the grasp planning systems that uses GQ-CNN.
The GQ-CNN prediction probabilities are used during an iterative sampling procedure to obtain the best grasp plan.
In consequence, a poor calibration of the predictions will result in a bad grasp plan. Furthermore, it is well known
that the modern deep neural networks often obtain poorly calibrated probability estimates [4]. Because of that, we
investigate the calibration of the obtained predictions and the impact of the data augmentations on the calibration.

Figure 3 shows that the predictions obtained without using the data augmentations show very poor calibration.
On the other hand, when the data augmentations are used the predictions are well calibrated. Therefore, without
the data augmentations the final grasping performance might be worse due to the poorly calibrated grasp sampling
procedure.
Figure 3: Impact of the data augmentations on the calibration of the GQ-CNN predictions for the image split. The upper subplot shows the calibration curves and the lower subplot shows counts of predictions for each bucket.

5 Conclusions

We proposed several improvements to the GQ-CNN grasp planning system. We devised a new network architecture for GQ-CNN that outperforms the original one. We enriched the data augmentation scheme which resulted in better generalization on the more challenging train/test splits. Finally, we showed that the data augmentation has a large impact on the calibration of the network predictions, which are crucial for finding robust grasps.

In the future will perform experiments on a real robot to validate whether our improvements on the synthetic data are reflected in a better grasping performance. Additionally, we are planning to further improve the GQ-CNN grasping system by generating a larger and more diverse training dataset, using higher resolution of the input images, and increasing the sampling efficiency of the grasping policy.

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References

[1] Jeannette Bohg et al. “Data-driven grasp synthesis—a survey”. In: *IEEE Transactions on Robotics* 30.2 (2014), pp. 289–309.

[2] Peter Brook, Matei Ciocarlie, and Kaijen Hsiao. “Collaborative grasp planning with multiple object representations”. In: *Robotics and Automation (ICRA), 2011 IEEE International Conference on*. IEEE. 2011, pp. 2851–2858.

[3] Renaud Detry et al. “Learning a dictionary of prototypical grasp-predicting parts from grasping experience”. In: *Robotics and Automation (ICRA), 2013 IEEE International Conference on*. IEEE. 2013, pp. 601–608.

[4] Chuan Guo et al. “On Calibration of Modern Neural Networks”. In: *arXiv preprint arXiv:1706.04599* (2017).
[5] Carlos Hernandez et al. “Team Delft’s Robot Winner of the Amazon Picking Challenge 2016”. In: arXiv preprint arXiv:1610.05514 (2016).

[6] Alexander Herzog et al. “Learning of grasp selection based on shape-templates”. In: Autonomous Robots 36.1-2 (2014), pp. 51–65.

[7] Sergey Ioffe and Christian Szegedy. “Batch normalization: Accelerating deep network training by reducing internal covariate shift”. In: International Conference on Machine Learning. 2015, pp. 448–456.

[8] Daniel Kappler, Jeannette Bohg, and Stefan Schaal. “Leveraging big data for grasp planning”. In: Robotics and Automation (ICRA), 2015 IEEE International Conference on. IEEE. 2015, pp. 4304–4311.

[9] Ben Kehoe et al. “Cloud-based robot grasping with the google object recognition engine”. In: Robotics and Automation (ICRA), 2013 IEEE International Conference on. IEEE. 2013, pp. 4263–4270.

[10] Diederik Kingma and Jimmy Ba. “Adam: A method for stochastic optimization”. In: arXiv preprint arXiv:1412.6980 (2014).

[11] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. “Imagenet classification with deep convolutional neural networks”. In: Advances in neural information processing systems. 2012, pp. 1097–1105.

[12] Ian Lenz, Honglak Lee, and Ashutosh Saxena. “Deep learning for detecting robotic grasps”. In: The International Journal of Robotics Research 34.4-5 (2015), pp. 705–724.

[13] Sergey Levine et al. “Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection”. In: The International Journal of Robotics Research (2016), p. 0278364917710318.

[14] Jeffrey Mahler et al. “Dex-net 1.0: A cloud-based network of 3d objects for robust grasp planning using a multi-armed bandit model with correlated rewards”. In: Robotics and Automation (ICRA), 2016 IEEE International Conference on. IEEE. 2016, pp. 1957–1964.

[15] Jeffrey Mahler et al. “Dex-Net 2.0: Deep Learning to Plan Robust Grasps with Synthetic Point Clouds and Analytic Grasp Metrics”. In: arXiv preprint arXiv:1703.09312 (2017).

[16] Lerrel Pinto, James Davidson, and Abhinav Gupta. “Supervision via competition: Robot adversaries for learning tasks”. In: Robotics and Automation (ICRA), 2017 IEEE International Conference on. IEEE. 2017, pp. 1601–1608.

[17] Lerrel Pinto and Abhinav Gupta. “Supersizing self-supervision: Learning to grasp from 50k tries and 700 robot hours”. In: Robotics and Automation (ICRA), 2016 IEEE International Conference on. IEEE. 2016, pp. 3406–3413.

[18] Florian T Pokorny and Danica Kragec. “Classical grasp quality evaluation: New algorithms and theory”. In: Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on. IEEE. 2013, pp. 3493–3500.

[19] Domenico Prattichizzo and Jeffrey C Trinkle. “Grasping”. In: Springer handbook of robotics. Springer, 2016, pp. 955–988.

[20] Joseph Redmon and Anelia Angelova. “Real-time grasp detection using convolutional neural networks”. In: Robotics and Automation (ICRA), 2015 IEEE International Conference on. IEEE. 2015, pp. 1316–1322.

[21] Alberto Rodriguez, Matthew T Mason, and Steve Ferry. “From caging to grasping”. In: The International Journal of Robotics Research 31.7 (2012), pp. 886–900.