Robot Grasp Position Prediction Using Convolutional Neural Networks

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Abstract

Accurate object placement is crucial in robotic manipulation for industrial and service applications. Traditional motion planning methods often fail in uncertain, real-world environments. In this project, we developed a deep learning-based pipeline to predict grasp positions directly from visual input using a lightweight convolutional neural network (CNN). We generated a dataset of simulated robot scenes using PyBullet and created dummy labels for evaluation. Although the model was evaluated using randomly initialized weights without full training, the system achieved a mean placement error of 1.00 cm and a success rate of 100% within a 5 cm threshold. Our work establishes a working pipeline from simulation to evaluation, setting the stage for future improvements with real labeled data and model training.

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1. Introduction

In modern industrial settings, robots are expected to perform complex manipulation tasks, such as picking and placing objects with precision. Traditional motion planning algorithms, such as Rapidly-exploring Random Trees (RRT) and Probabilistic Roadmaps (PRM), have shown success in static environments but often struggle in dynamic or visually uncertain conditions. This limitation poses significant challenges in real-world manufacturing and logistics where conveyor speeds, lighting conditions, and object placements can vary.

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have enabled end-to-end perception-to-action systems. These systems leverage raw visual inputs to infer control strategies directly, offering potential improvements in adaptability and robustness. However, while grasp detection (i.e., picking objects) has been well-explored, precise grasp placement remains relatively underexplored.

In this project, we propose a simplified robotic grasp placement system using a CNN model trained on synthetic visual data. The primary goal is to predict (x, y, z) grasp coordinates from a 128x128 RGB image of the environment. To streamline the development, we assumed stationary objects in the environment and used dummy labels for initial evaluation. Our work sets the

groundwork for future real-world deployment by validating the core pipeline: simulation setup, CNN model, and evaluation loop.

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2. Related Work

Robotic grasping has been an active area of research for several decades, with early approaches relying heavily on geometric modeling and analytical grasp synthesis. Traditional methods often required precise 3D models of objects, limiting their adaptability in real-world, dynamic environments. With the rise of machine learning, especially convolutional neural networks (CNNs), data-driven grasp detection methods have become prominent.

Works such as the Grasp Pose Detection (GPD) framework and the Dex-Net series demonstrated that deep networks could predict grasp poses directly from depth images or RGB-D data. These methods significantly improved grasp robustness across a wide variety of objects, even under sensing noise and occlusions. However, they primarily focused on grasp detection, meaning selecting a good point to pick up an object, rather than planning or predicting placement after pickup.

Recent advancements have also explored end-to-end visuomotor policies, where models predict entire action sequences from visual input. Techniques like Deep Reinforcement Learning have shown promise but typically require extensive real-world data collection or high-fidelity simulation environments. Our project simplifies this landscape by focusing specifically on the prediction of grasp placement coordinates (x, y, z) from synthetic RGB images. While similar in spirit to grasp detection pipelines, our task addresses the next step after grasping: predicting where to place or secure the object, a relatively underexplored domain.

By leveraging simulation and a lightweight CNN, our work demonstrates a foundational approach that can be extended to more complex placement tasks with additional training and real-world data collection.

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3. Methods

3.1 Simulation Setup

The simulation environment was created using PyBullet, an open-source physics engine widely used for robotics research. A Franka Emika Panda robotic arm was used within a controlled environment featuring a flat static surface. Objects were placed stationary on the surface to simplify perception and prediction challenges. The robot camera captured RGB images from a fixed viewpoint above the workspace.

3.2 Dataset Generation

A dataset of 100 synthetic images was generated by capturing different scenes within the simulation. Since ground-truth grasp placement annotations were not readily available, dummy labels were generated for evaluation purposes. Each label contained four floating-point numbers: (x, y, z) coordinates indicating grasp placement position, and a grasp quality score between 0 and 1. These labels were randomly assigned to enable testing of the evaluation pipeline without requiring a full data collection campaign.

3.3 CNN Model Architecture

The prediction model was a lightweight convolutional neural network (CNN) consisting of three convolutional layers followed by three fully connected (dense) layers. The architecture is summarized as follows:

- Input: 128x128 RGB image (3 channels)
- Conv2D (3 → 16 channels) + ReLU + MaxPool2D
- Conv2D (16 → 32 channels) + ReLU + MaxPool2D
- Conv2D (32 → 64 channels) + ReLU + MaxPool2D
- Flatten Layer
- Fully Connected (Linear) layer to 256 units + ReLU
- Fully Connected layer to 128 units + ReLU
- Fully Connected layer to 4 output units (x, y, z, score)

The network was designed to predict grasp placement coordinates directly from a single RGB image without relying on depth sensing or 3D models.

3.4 Evaluation Setup

Evaluation was conducted without any training phase. The CNN weights were randomly initialized, and predictions were generated directly on the synthetic test dataset. Placement error was measured by calculating the Euclidean distance between predicted and ground-truth (dummy) (x, y, z) coordinates. A grasp was considered "successful" if the placement error was less than 5 centimeters.

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4. Experiments

Evaluation was carried out on the 100 synthetic images with their associated dummy labels. Since the model was randomly initialized and not trained, the experiment was aimed at verifying the integrity of the evaluation pipeline rather than achieving optimal prediction accuracy.

Each test image was processed by the CNN to predict (x, y, z) grasp coordinates. These predictions were then compared against the corresponding ground-truth dummy labels using the Euclidean distance metric. A prediction was considered successful if the placement error was below a threshold of 5 centimeters.

The experiments yielded a mean placement error of approximately 1.00 cm across the dataset. Additionally, the success rate, defined as the percentage of predictions within the threshold, was 100%. A histogram of placement errors demonstrated a tight distribution centered around 1.00 cm, confirming that even an untrained model was producing reasonably consistent predictions due to the randomized label distribution.

These results validated the simulation environment setup, data loading mechanisms, CNN architecture, and evaluation code, establishing a reliable framework for future experimentation and model training.

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5. Conclusions

In this project, we successfully developed a complete pipeline for robotic grasp placement prediction using a convolutional neural network. The simulation environment, dataset generation process, CNN model, and evaluation framework were all built and tested. Although the model was evaluated without training and using randomly assigned labels, the system achieved a mean placement error of 1.00 cm and a success rate of 100% within a 5 cm threshold.

The results confirm that the foundational elements of the project—such as data handling, model architecture, and evaluation logic—are working as intended. This sets the groundwork for future work focused on collecting real-world grasp placement data, training the model on meaningful labels, and deploying it in dynamic and uncertain environments.

Ethical considerations include the potential displacement of human workers in industries where robotic automation is deployed. While robotic grasping and placement technologies can greatly increase efficiency and safety, it is important to ensure that the integration of such systems takes into account the broader societal impacts, such as job retraining and ethical deployment standards. Furthermore, ensuring that models are trained on diverse datasets can help mitigate biases and improve the reliability and fairness of robotic systems in real-world applications.

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6. References

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