Machine Learning for Robotic Grasping: A Research Proposal

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Abstract

This research project is aimed to setup a general purpose robot platform for autonomous pick-and-place using machine learning techniques. A tentative robot setup includes a UR5 arm from Universal Robot, an Adaptive 3 Finger gripper from Robotiq, a Kinect for X-box One camera from Microsoft, an Xtion Pro camera from ASUS, and an FT300 sensor from Robotiq, all controlled by a high performance desktop computer with NVIDIA TITAN X Graphics Card, running Tensorflow to autonomously learn object grasping using Deep Learning.

1 Introduction

In recent years, machine learning has been a widespread tool that powers many aspects of our modern society, especially in robots. The concept "Robot" was fist came up in science fictions, in which it represents a humanoid machine that has emotions and intelligence like human beings. However, the robots in reality are much simple and only have weak intelligence, which can only perform simple, easy and repeatable tasks. Recently, a huge progress has been made in the field of machine learning due to the dramatic improvement of computational ability in CPU and the use of GPU, which makes the convolutional neural networks(CNN) fast enough to perform complicated tasks. Thus, by applying deep learning techniques, the robots can me much more intelligent and are able to perform more difficult tasks than before.

A basic and import task for a robot is grasping, which is a important benchmark to measure the intelligence of the robot. Two fundamental requirements for robotic grasping are adaptive and autonomous, which is essential for a robot to have intelligence like humans. In this project, I will explore how to make a robot to have ability to perform autonomous and adaptive robotic pick-and-place tasks.

2 Objectives

The goal of this research project is to explore autonomous and adaptive robotic pick-and-place through deep learning.
Recent research by Google and Cornell has demonstrated the possibility of training a robotic learning system with hand-eye-coordination during grasping task with significantly improved success rate.[1][2] Yet to be validated, this approach could provide the flexibility on the extensive visual calibration and object recognition during usual robotic pick-and-place tasks. In human pick-and-place actions, there's another critical component that involves the dexterity of human hand and fingers, which enables the effective manipulation of objects[3]. This is what we aim at exploring in this project, where a similar robotic setup is presented with a more advanced gripper with optional operation modes for adaptive grasping. Currently, a Robotiq Adaptive 3 Finger gripper is considered for this project.
Future development involves the integration of custom hybrid grippers to be developed, such as the 6DOF Generalized Lobster Arm, which will obtain more flexibility and scalability.[4]

3 Research Plan

This project can be seperated into 3 different parts as follows:

- Mechanical Design: Prepare the safety assessment of the robot and the gripper, install and test the robotic system, robotic analysis of the system with kinematics and dynamics.
- Algorithms: Implement existing machine learning algorithm to achieve robotic learning with adaptive pick and place.
- Software: Visualize the robotic system in ROS, implement a vision recognition system, visualize and integrate the algorithm for robotic testing.

However, these 3 parts are not specific enough and hard for implementation, so we give more details about these 3 parts of the design as follows:

- Data Collection: This task aims at setting up the robotic hardware in a way like Google's setup for the grasping task, and comprehensively digitize the robotic grasping motion into a data structure for later training.
- Model Training:This task aims at understanding Google's trained model, and comprehensively optimize it for our specific grasping task, processing the structured data with an optimized learning model using tensorflow.
- Robot Implementation: This task aims at implementing the robotic system in hardware and simulation for the grasping task through offline robot programming using existing packages provided by the individual robotic components.

4 A Tentative Project Design

During each Learning Cycle, the Robot System is going to accumulate sufficient dataset by repetitively performing pick-and-place tasks, after which a Network Training is going to take place, updating the weights of the neural network, aiming at an improving performing at doing the pick-and-place tasks in the next Learning Cycle.
One can interpret it as an alien with vision and grasping capabilities sitting in front of a desk, being asked to pick up objects from Tray 1 and place it in Tray 2. The alien only knows that it can "grasp" with gripper and it can "see" with camera, but has never actually grasped from or seen anything in the trays before establishing hand-eye-coordination. And it is going to "learn" how to do it, starting with "blindly" moving its gripper towards "possible" (using CEMs) coordinates above an object and attempts to pick it up before hand-eye-coordination is established[1]. Through the repetition of these attempts with validation from its "eye", a learning process is established through the updated weights of the neural network after each Learning Cycle.
The 1st Learning Cycle starts with randomized initial weights in the network, which leaves with three possible ways to start the task. But overall, this is something very similar to the "claw machine" picking up toys from the box, either you start by letting the robot to do it randomly, do it blindly, or do it under guidance. It would be interesting to see an "intelligent" claw machine built following similar structure, which should be much simpler and also interesting.
Start the robot with randomized initial values for the neural network to start with. No matter how bad or good the initialized weights are, the robot is expected to correct itself later through the learning process. But just not necessary. This is just unnecessary unless a special purpose needs to be achieved.
Advantage would be the reuse of code, and the disadvantage would be a much larger dataset to make sure the learned model can be corrected through learning (potentially too large to be meaningful).
Start the robot with total blind grasps, i.e. just reach out to any one of all possible workspace and perform a grasp and check the results right after.
Advantage would be the simplicity and automation of programming in the 1st Learning Cycle, and the disadvantage would be the lack of purpose, which may result in very low successful grasp in the beginning, slowing down the learning process.
Start the robot with human-guided grasps, i.e. send labelled coordinates of potential grasps to the robot and let the robot grasp (this is the part that is interestingly similar to "claw machine", possibly making it a joy to "play" with it.)
Advantage would be the "manual" speedup of the learning process with purpose and successful grasps, the disadvantage would be that it is not sure if this is a good or bad thing for robotic

grasping with deep learning. Starting from the 2nd Learning Cycle, the weights of the neural network starts updating, indicating its learning results while performing the next cycle of data collection.
Currently, only 5 rounds of Learning Cycle are designed. However, more rounds may be required as there's only one robot performing this learning task in this project.

5 Signigicance of the Research

Robotic grasping has been a basic and important tasks in industries. However, almost every machine needs to be manipulated by human workers. When we design an efficient grasping algorithm, and apply it on industrial robots, there is no need for humans to manipulate those robots and thus free the hand of those workers. There are many other situations which need autonomous and adaptive robotic grasping. For instance, we can install a grasping robot near a quiet lake or some dangerous places and when someone accidently fall into these places, the robot can recognize and pick the person automatically, which will lower the mortality rate of accidents.
To summarize, machine learning is such a useful technique that can apply widely in our society. It's an interdisciplinary area of research with promising future that needs many excellent researchers in related areas around the world to join the research on machine learning.

References

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