

Recognition and Detection of Objects and Their Position for Robotic Grip Decision

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Abstract

The modern world demands high variability of products with high customization. Fast paces of technical development made small computing devices and robots available for small companies, but what is left out of the scene is a new framework for small companies to utilize the robots for custom orders. This can be easily done with the unique framework that allows robots to use low-cost cameras and machine learning (ML) models to detect the objects, their position and decide how to grasp the object. This allows the user to load the pile of parts on the "table" and let the robot assemble the product. In this paper, I attempt to tackle this problem using Raspberry PI and robots available at NCSU ISE labs.

Keywords: position detection; grip decision for the robot; raspberry pi; low-cost camera; YOLO

1. Introduction

The modern world demands high variability of products with high customization [1]. Humans can produce products with significant variability, while automated lines are better suited to repetitive, monotonous work. On the other side, robots outperform human workers in speed, quality level, and labor cost. The optimal employee is a robot that can adjust to the environment and fast-changing objectives. This can be achieved through the implementation of machine vision and decision-making based on the retrieved information.

People work alongside robots, and this imposes a challenging task for robotics developers. The machines must be aware of surrounding objects, adjust to the part's non-standard orientation and know how to use them. Current technological progress rates bring the prices for computing devices really low, leading to widespread 'Smart' devices worldwide. Raspberry PI (RPI) is the corollary of this progress; more than 20 million of these low-cost computers have been sold worldwide [2]. Robotic vision systems can be built using RPIs and low-cost cameras. Many DIY materials on the internet show how to create simple object recognition and detection systems [3]–[5].

Object recognition is not a problem nowadays: different ML models outperform humans in object recognition accuracy [6], [7], and speed [8]. Nevertheless, they are either slower in the first case or not as accurate in the second case. Some commercial "Smart" cameras exist that have both advantages at the cost of a high price.

This paper aims to develop a prototype of a machine vision system that will consist of relatively cheap components and recognize the objects located in front of a camera. This system has to work quickly to timely decide how to grab the part with a mechanical grip.

2. Related work

There are different approaches to how the ML system decides which object is in front of it and its current position. [9] implemented a two-stage recognition approach. In their work, they used The Cornell Grasping Dataset [10], where the first stage was to detect the object and feed the result to the next model. The second stage defines the gripping area based on the detected object and the corresponding gripping area available for this object. Tsarouchi et al. [11] used a different approach where the object was predefined, but its position varied. They created labels for the predefined positions and used the ML model to extract a binary image and classify the position. This approach looks very robust in serial production, where the objects for the handling are not varying wildly. Besides, this approach utilizes 3D CAD model that corresponds to the position. Based on this information, the system decides how to grab the object. Kaymak et al. [12] implemented the actual performing prototype that was able to recognize objects, grab them and locate them in the desired bin. The drawback of this work is that the objects were simple, and the Z coordinate was fixed. Chatterjee et al. [13] used the modified YOLOv3 model to install it into a low-computing humanoid robot. It was capable of detecting the objects with high accuracy and speed. This work is a practical implementation of machine vision systems for simple and relatively cheap hardware. Pillai [14] developed a SLAM-supported object recognition system that improves the recognition based on time accumulated data. It outperforms the frame-based recognition in accuracy and provides the possibility to use a single camera to calculate the distance and update the information for the grip decision.

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