Chapter 8

Ellipse Detection-Based Bin-Picking Visual Servoing System

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ABSTRACT

In this chapter, the authors tackle the task of picking parts from a bin (bin-picking task), employing a 6-DOF manipulator on which a single hand-eye camera is mounted. The parts are some cylinders randomly stacked in the bin. A Quasi-Random Sample Consensus (Quasi-RANSAC) ellipse detection algorithm is developed to recognize the target objects. Then the detected targets’ position and posture are estimated utilizing camera’s pin-hole model in conjunction with target’s geometric model. After that, the target, which is the easiest one to pick for the manipulator, is selected from multi-detected results and tracked while the manipulator approaches it along a collision-free path, which is calculated in work space. At last, the detection accuracy and run-time performance of the Quasi-RANSAC algorithm is presented, and the final position of the end-effector is measured to describe the accuracy of the proposed bin-picking visual servoing system.

INTRODUCTION

Most of the manipulators practically used in industry operate in an open-loop mode. Their motions need to be programmed off-line or taught by operators, and the environment should be organized to suit them. In order to increase the flexibility and the accuracy of robot system, visual feedback control or visual servoing was introduced and widely researched. Typically, the visual feedback control system is classified into two groups: Position-Based Visual Servoing (PBVS) and Image-Based Visual Servoing (IBVS) (Seth, Gregory, & Peter, 1996; Danica & Henrik, 2002;
Both in position-based and image-based visual servoing process, the vision system extracts features of the target object in the image to provide input to the robot controller. The features could be points, lines, planes, regions, etc. Then in position-based visual servoing, three-dimensional information of the target object is estimated with respect to the camera (robot, world) coordinate system (Danica & Henrik, 2002). The aim is to steer the manipulator’s end-effector towards the target object in the task of picking, assembling, etc. While in image-based visual servoing, the main objective is to keep the features at a desired position in the 2D image plane (Bernard, Francois, & Patrick, 1992; Jenelle & Harvey, 2003).

The task of our bin-picking system is to pick parts (cylinders) from a bin. Hence, it is a position-based system. Our work is a further development of (Hao, Sun, & Fujii, 2007), where the detection and measurement method and visual servoing control algorithm to approach the cylinder were researched, and the experiments with an industrial 6-DOF manipulator with a hand-eye camera validated the proposed method. However, condition was simplified to only one horizontally placed target. In real industry, the most likely condition is that many objects of the same shape are stacked randomly in a container or a bin. Under this condition, the manipulator has to recognize and select one target for handling and avoid obstacles, e.g. the wall of the bin and other objects.

To recognize the cylinder targets, ellipse feature is used. There are mainly two types of ellipse detection methods: Hough transform based algorithms (Nair & Saunder, 1997; Guil & Zapata, 1997; Robert, 1998), and geometric methods (Hao, Sun, & Fujii, 2007; Ho, & Chen, 1995; Song & Wang, 2007). The Hough transform methods are computationally expensive and unsuitable for real-time control, so we choose geometric method. To improve the detection result’s stability of the method in (Hao, Sun, & Fujii, 2007), a Quasi-Random Sample Consensus (Quasi-RANSAC) method is developed in this chapter.

**QUASI-RANSAC ELLIPSE DETECTION**

Since we choose cylinder as target object, and the projection of cylinders in image are some ellipses, so the target detection task is boiled down to ellipse detection task. The detection result is organized as

$$e_{i} = [x_{i}, y_{i}, a_{i}, b_{i}, \theta_{i}]$$ (1)

where \((x_{i}, y_{i})\) denote the coordinates of ellipse center in image, \((a_{i}, b_{i})\) are its semi-major axis and semi-minor axis, and \(\theta_{i}\) denotes its orientation angle. They are all the information about the target that the robot controller can utilize. The ellipse detection algorithm is based on the continuous edge feature which is called a contour (Cai, Yu, & Wang, 2004). In this way, we only regard the contour as a candidate of ellipse rather than all the edges in the edge image which cost lots of computation and memory.

The RANSAC algorithm is an effective method for model fitting (Fischler & Bolles 1981). In (Hao, Sun, & Fujii, 2007), the method was used to detect ellipse, but the detection results were not that stable. This is mainly because that the five points used to fit the ellipse are randomly sampled from the contour. The unstable ellipse will later lead to robot’s motion error. In order to overcome this shortage, we change the sample strategy from random to quasi-random. Namely, we select the first point randomly while the other four points are uniformly distributed on the contour with respect to the first point, and ten groups of 5-point are sampled. For each group, an ellipse is fitted if could, using the Analytic Geometry Theory Based Ellipse Fitting method (Hao, Sun, & Fujii, 2007), and an average ellipse is computed from the fitted ellipses. Then the Mean Square Error (MSE) between the average ellipse and the candidate contour is computed. If the error is less
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