Crop Recognition Method Based On End-effector

Ruoyu Wu
Department of International, Jinan University, Guangzhou, China
2015141496051@stu.scu.edu.cn

Abstract. With the increasing global population, the demand for agriculture is also on the rise. The crucial stages of agricultural production, namely fruit identification and picking, play a vital role in enhancing product quality and minimizing losses. Traditional manual processing methods, although time-tested, are not only inefficient but also challenging to maintain consistency, making them inadequate to meet the large-scale requirements of modern agricultural production. Consequently, the integration of automation technology has become a necessity. For agricultural robot the machine vision system often need to work in two typical environments, the field environment and the orchard environment. Depending on the varying objectives of operation in diverse environments, crop robots require the ability to rapidly identify fruits within images featuring significant color disparities between crops and two-dimensional field backgrounds. Consequently, a visual servo control system is being investigated. A novel camera attitude search method that employs active visual servo technology to minimize occlusions during orchard search is proposed. The recognition function of the end-effector is exceedingly crucial. The precision of the end effector's identification capabilities directly influences the success rate of automated operations. This is particularly evident in fruit picking, sorting, and other tasks, where the diverse shapes, maturity levels, and colors of fruits present significant challenges to the robotic arm's end effector. The rapid advancement of deep learning technology, however, offers a novel solution for the recognition of fruits by the robotic arm's end effector. By emulating the human visual system, deep learning models can extract the feature representation of fruits from vast amounts of data, enabling accurate identification of fruits in various conditions.

Keywords: Agriculture; vision servo; end-effector.

1. Introduction

In recent years, the utilization of picking robots has gained significant global attention, with notable advancements in research and development observed in countries such as the United States, Japan, the United Kingdom, and France [1]. The emergence of these robots has revolutionized the agricultural industry by automating the labor-intensive process of fruit picking, thereby enhancing efficiency and reducing costs.

One of the pioneering studies in this field was conducted in 1994 by Edan et al [2]. Who focused on exploring the characteristics of a five-degree-of-freedom picking robot. This robot stood out for its exceptional dexterity and precision, being specifically designed to effortlessly perform various picking tasks. To ensure operational efficiency and accuracy, machine vision technology was employed by researchers to accurately identify fruits - a critical capability.

Furthermore, Edan et al. also achieved three-dimensional fruit positioning - a significant breakthrough that enables precise grasping of fruits while minimizing damage risks and improving overall harvest quality. This development marks a crucial milestone towards automating fruit-picking processes while paving the way for further research and innovation within this domain.

In 2018, Weikuan Jia et al. examined the pre-processing technique employed for Apple's night vision imagery [3]. They selected three distinct artificial light sources to capture night vision images of apples and utilized color analysis and differential image methods to facilitate night vision perception of the apples' View image preprocessing. Qinghua Yang et al. devised a rapid recognition and stereoscopic localization strategy for chrysanthemum Dharma [4]. In this approach, a swift fuzzy C-means algorithm was employed to extract the target image, which was derived from stereo vision technology, to obtain spatial data of Hangzhou white chrysanthemum. Lufeng Luo et al. engineered a six-degree-of-freedom serial picking robot for operation under dynamic and uncertain environments [5].

The intricately woven tapestry of a strawberry plantation is ingeniously captured in the compilation of images, which exclusively highlights the vibrant fruit. Besides the intrinsic details, an array of influencing factors also grace the frame, including the lush leaves, sinewy branches, and the ethereal sky. The captured image is further enriched by the interplay of climatic conditions, lighting, and the distinct growing season, among numerous other non-human factors. A strawberry picking robot is currently under design, primarily focusing on the implementation of the executive end and the visual servo system, which will revolutionize the agricultural landscape.

2. End-effec

The end-effector is composed of a manipulator that possesses six degrees of freedom, Each joint of the manipulator generates a coordinate transformation of two translations and two rotations, and the transformation relationship of the adjacent coordinate system can be represented by its transformation matrix. The coordinate system of connecting rod I-1 can be transformed into the coordinate system of connecting rod i after two rotations and two translations. These four transformations are represented by a matrix respectively, and then multiplied to obtain the transformation matrix of adjacent joints.

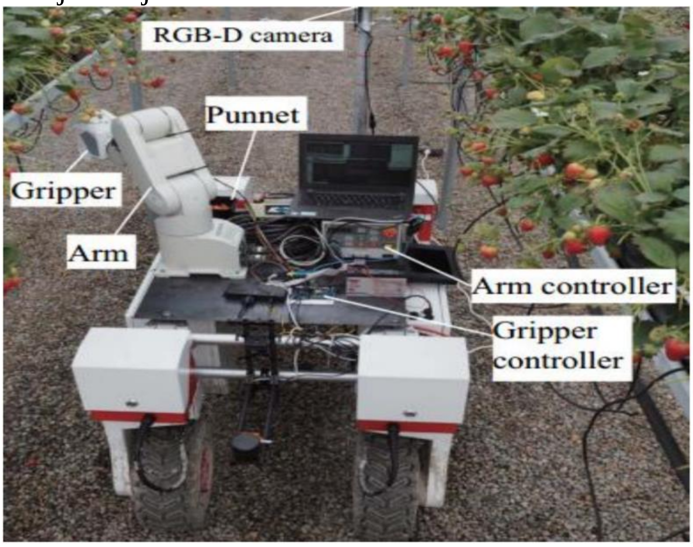

Fig. 1 Picking Robot Designed by Norwegian University of Life Sciences [6]

According to Figure 1 agricultural picking robot designed by Norwegian University of Life Sciences, understand the approximate robot construction.

For the improved D-H method, the transformation matrix can be expressed as:

$$ {}^{i-1}T_i = \mathrm{Trans}_x(a_{i-1})\mathrm{Rot}_x(a_{i-1})\mathrm{Trans}_z(d_i)\mathrm{Rot}_z(\theta_i) = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i) & 0 & a_{i-1} & \\ \cos(a_{i-1}) & \sin(\theta_i) & \cos(a_{i-1})\cos(\theta_i) & -\sin(a_{i-1}) & -d_i\sin(a_{i-1}) \\ \sin(a_{i-1}) & \sin(\theta_i) & \sin(a_{i-1})\cos(\theta_i) & \cos(a_{i-1}) & d_i\cos(a_{i-1}) \\ 0 & 0 & 0 & 1 & \end{bmatrix} \tag{1} $$

We are aware of two typical visual servo control strategies: image-based and position-based visual servo control [7]. The camera can be directly mounted on a robot manipulator or a mobile robot, where the movement of the robot causes camera motion. Alternatively, the camera can be stationary in the workspace to observe the motion of the robot from a fixed configuration.

The aim of all vision-based control schemes is to minimize an error e(t), which is typically defined by e(t) = s(m(t), a) − s∗ [8].

The parameters are defined as follows: The vector m(t) represents a collection of image measurements, such as the coordinates of points of interest or the centroid coordinates of an object in the image. These measurements are utilized to calculate a vector s(m(t), a) consisting of k visual features. Here, parameter set a is employed to incorporate additional knowledge about the system, such as coarse camera intrinsic parameters or 3-D models of objects. The desired values for these features are contained within vector $s*$.

3. Vision Servo

This work employs a camera that is mounted directly on the robot manipulator arm, called eye in hand. The application of visual servo technology enables the recognition of strawberry ripeness and the tracking of the robotic.

3.1. RGB-D Image Recognition

The RGB-D sensor integrates traditional RGB sensors and depth sensors, enabling it to capture not only the color information of objects but also their spatial depth information. During the strawberry picking process, this sensor helps robots accurately identify the location, size, and ripeness of strawberries, facilitating automated picking.

Firstly, the RGB-D sensor provides color information about the strawberry. While strawberries are typically red, the shade and tone of the color may vary under different lighting conditions. By capturing the color information of strawberries and combining it with color histogram and texture features, the RGB-D sensor can effectively recognize ripe strawberries. For instance, in the paper "A Real-Time Vision-based System for Strawberry Harvesting," the authors propose a real-time Vision system that accurately recognizes ripe strawberries by analyzing color histograms and texture features.

Secondly, the addition of depth information allows the robot to perceive the distance between the strawberry and its surroundings. This is crucial for planning the picking path and avoiding damage to the fruit. In the article "Design of a Robotic Strawberry Picking System Using RGB-D Sensors," researchers use RGB-D sensors to obtain depth images of strawberries and combine machine learning algorithms to process the depth information. This enables the accurate estimation of strawberry position and the planning of picking actions, allowing the picking robot to grasp and separate strawberries without touching other plants.

Furthermore, the RGB-D sensor helps robots maintain stable performance in variable lighting conditions. In the study "Strawberry Picking Robot with RGB-D Camera under Variable Lighting Conditions," researchers investigate how the RGB-D sensor aids the robot in stably recognizing strawberries under different lighting environments.

3.2. Strawberry Ripeness Recognition

To implement an effective visual servo system, we have developed a framework using MATLAB, which amalgamates the functionalities of image acquisition and robot control. This system is designed to process images in real-time, captured through cameras, and to identify objects based on specific color criteria. Upon recognizing an object, the system employs inverse kinematics algorithms to adjust the posture of a 6-DOF (Degrees of Freedom) robotic arm. This adjustment is based on the centroid position of the identified object, thereby facilitating accurate interaction between the robot and the object.

Image-based visual servo control is governed by the definition of error signals within the two-dimensional image plane, obviating the need for utilizing the three-dimensional pose information of the mobile robot. This approach exhibits robustness against system disturbances, albeit it poses challenges in controlling the deflection pose of the mobile robot. On the other hand, position-based visual servo control necessitates the definition of error signals in the three-dimensional Euclidean space. Although it necessitates three-dimensional weighting, the direct control of errors in three-dimensional space ensures its convergence.

The calibration process is a crucial step in enhancing the accuracy of captured images by optimizing the performance of a monocular camera through meticulous calibration procedures that utilize both internal and external parameters. The beam method (forward intersection) plays a pivotal role in facilitating image adjustment, enabling computation of accurate three-dimensional coordinates of the target object. By accounting for factors such as lens distortion, sensor non-uniformity, and camera motion, the calibration process produces high-quality image data that enhances computer vision algorithms and other applications reliant on accurate image data.

Subsequently, the visual servo mechanism at the terminal oof the machine is implemented for practical usage.

The practical application of this visual servo system is exemplified through the operation of a three-claw robot, designed to perform precise grasping tasks. The process involves several steps:

1) Initially, the claw's opening position is set such that the angle of the sixth joint (L6) is at 0 degrees for an open paw, and at 30 degrees for a fully closed paw.

2) Subsequent to the robotic arm's target location and joint angle calculation, a logic control mechanism is employed to facilitate the claw's closing action, thereby enabling the grasping of the target object.

3) Upon successful grasping, the robotic arm is programmed to perform additional maneuvers to lift and relocate the target to a predetermined destination.

This comprehensive approach to visual servoing not only underscores the integration of computer vision and robotic control but also highlights the potential for enhanced interaction and manipulation capabilities within robotic systems.

Our investigation into the automation of agricultural processes has led to the development of a sophisticated strawberry ripeness recognition system, utilizing Convolutional Neural Networks (CNNs). The system harnesses the power of two prominent CNN architectures, ResNet-50 and VGG16, to accurately classify strawberries into various stages of ripeness. A comprehensive dataset, consisting of meticulously annotated images of strawberries across different ripeness levels, was compiled to train and validate the models, ensuring a robust evaluation of their performance.

3.3. Robot Tracking

If the previous fruit picking is more based on image visual control, then path recognition is based on location visual control. The calculation of the robot's current position relies on perspective lines that define the navigation path. Robot tracking plays a crucial role in autonomous navigation systems, enabling robots to navigate through environments with precision and efficiency. A prominent method for achieving such autonomy is through implementing image-based techniques...

Rephrased: The initial challenge in strawberry picking is to find a collision-free route within the orchard environment. Currently, there are two primary approaches for path planning: global path planning based on models and local path planning based on sensor input [9]. This study employs a local path planning technique utilizing artificial potential fields.

The approach to path planning, proposed by Khatib, utilizes artificial market principles and employs a virtual force technique. This method involves converting the motion of robots in their surrounding environment into an abstract gravitational field created artificially.

The RRT algorithm is comprehensive. Provided there are sufficient sampling points, an executable path can be devised and obstacles can be circumvented to a certain degree. Nonetheless, there are also inherent limitations. If the algorithm is executed for an extended period, the search scope is overly broad, or the number of obstacles in the space is excessively large, it will extend the time required for path planning. To abbreviate the time spent on searching the state space, it is imperative to specify the fixed path of the picking robot, and initiate the construction of random obstacles simultaneously from the starting point and the endpoint.

Given that the problem of trajectory tracking control for mobile robots involves a time-varying affine nonlinear system, Adaptive Dynamic Programming (ADP) proves to be an effective approach for solving nonlinear optimal control problems. ADP is an intelligent control method that can effectively address the issue of "dimensionality disaster" in traditional dynamic programming and handle complex constraints and uncertainties. It exhibits self-adaptability, optimality, and stability when dealing with complex nonlinear systems characterized by significant nonlinearity and strong coupling.

4. Discussion

Compared with the traditional manual picking method, the picking robot offers numerous advantages that make it a valuable asset in modern agricultural production. With its higher technical content and stronger intelligent ability, the robot brings automation, high efficiency, and high precision to the process of crop harvesting.

One of the key benefits of using picking robots is their ability to adapt to the needs of modern agriculture. They can be programmed to handle various crops and adjust their picking techniques accordingly. This flexibility allows farmers to optimize their production processes and meet market demands more effectively.

However, it is important to acknowledge that picking robots also face certain limitations. One such limitation lies in their recognition and positioning accuracy. Picking robots rely on computer vision technology to identify and locate target crops. Unfortunately, factors like lighting conditions, angles, occlusion from other objects or plants can affect their performance in terms of accurate positioning. This may result in lower positioning accuracy or misidentification issues which ultimately reduce overall picking efficiency.

To overcome these challenges, manufacturers often equip picking robots with high-precision sensors, controllers, actuators, and other advanced equipment. These components not only enhance performance but also contribute significantly to manufacturing costs. Additionally, maintenance and debugging processes require specialized expertise which adds further expenses.

Furthermore, another aspect where picking robots struggle is adapting to complex environments. Agricultural fields are dynamic spaces with varying terrains and unpredictable obstacles such as uneven ground surfaces or unexpected plant growth patterns. Picking robots need continuous advancements in design and technology integration for better navigation capabilities within such challenging environments.

In conclusion, while there are undeniable advantages associated with using picking robots for agricultural purposes including automation capabilities along with increased efficiency and precision; they do encounter limitations related primarily to recognition accuracy as well as difficulties operating within complex environments due to cost constraints associated with advanced equipment requirements during manufacturing stages along with subsequent maintenance expenses involved [10].

Picking robots play a crucial role in the agricultural industry by automating the process of identifying and locating target crops. However, they face challenges due to various factors such as lighting conditions, viewing angles, occlusion, and more. These factors often lead to low positioning accuracy and misidentification issues, ultimately resulting in reduced picking efficiency.

To overcome these challenges, picking robots typically require advanced computer vision technology that can adapt to different environmental conditions. This involves equipping them with high-precision sensors capable of capturing accurate data about the crops' location and characteristics. Additionally, controllers and actuators are essential components that enable precise movements for efficient crop picking.

However, it is important to note that the integration of such sophisticated equipment increases the manufacturing cost of these robots significantly. The need for precision sensors, controllers, actuators, and other specialized components adds up to their overall production expenses. Moreover, post-production maintenance and debugging also incur additional costs.

Despite advancements in technology and engineering efforts aimed at reducing costs without compromising performance quality or reliability levels remain a challenge. Picking robots must be able to operate effectively in complex environments where there may be unpredictable obstacles or variations in crop appearance due to growth stages or external factors like weather conditions.

In conclusion, while picking robots offer immense potential for improving agricultural productivity through automation technologies like computer vision systems; they still face hurdles related to positioning accuracy limitations caused by lighting conditions or occlusions during operation. Furthermore, the high manufacturing cost associated with equipping them with advanced sensors/controllers/actuators along with subsequent maintenance expenses pose financial challenges for widespread adoption across diverse farming environments

5. Conclusion

This study employs strawberry picking as a case study to investigate agricultural picking robots, and has designed a 6-DOF manipulator-based picking robot system. Building on this foundation, digital image processing techniques are utilized to accomplish the identification and localization of strawberries, as well as the path planning for the picking robots utilizing the RRT algorithm. The method entails the application of the inverse motion learning algorithm, camera capture, and RGB-D image recognition to identify specific objects and their maturity levels based on specific color standards. Ultimately, this approach enables the precise acquisition of real-time positional information for strawberry crops. This information is then used to accurately control the robot's movements and navigate around obstacles. This study examines the current state of precision strawberry picking in agriculture, with a focus on the varying maturity levels, and summarizes the application status of deep learning technology in image processing and pattern recognition. By enabling efficient and accurate identification of fruits via the end effector of the robotic arm, based on deep learning, labor costs can be reduced, and operational efficiency improved in automated picking, sorting, and other processes. This development has the potential to facilitate and ultimately promote the advancement of automation and artificial intelligence in agricultural sectors.

References

[1] Li Zhankun. Research and Design of Fruit tree Picking Robot Control System [D]. Jiangsu University. 2010.

[2] Edan, Y., Gaines, E. Systems engineering of agricultural robot design[J]. IEEE Transactionson SystemManufacture. 1994, 24(8):1259–1265.

[3] Weikuan Jia, Yuanjie Zheng, De’an Zhao, Xiang Yin, Xiaoyang Liu, Ruicheng Du. Preprocessing Method of night vision image application in apple harvesting robot[J].International Journal Agricultural&BiologyEngineering, 2018, 11:54-56.

[4] Qinghuang, Chang, Guanjun Bao, Jun Fan, Yi Xun. Recognition and local ization system of The robot for harvesting Hangzhou White Chrysanthemums[J]. International Journal Agricultural & Biology Engineering, 2018, 11:34-40+79.

[5] Lufeng Luo, Hanjin Wen, Qinghua Lu, Haojie Huang, Weilin Chen, Xiangjun Zou, Chenglin Wang. Collision-Free Path-Planning for Six-DOF Serial Harvesting Robot Based on Energy Optimaland Artificial Potential Field[J]. Complexity, 2018, 35:33-35.

[6] Lili Zhao, Agricultural picking robot based on visual recognition System research

[7] S. Hutchinson, G. D. Hager and P. I. Corke, "A tutorial on visual servo control," in IEEE Transactions on Robotics and Automation, 1996, 12(5), 651-670.

[8] Chaumette, F., & Hutchinson, S. (2006). Visual servo control. I. Basic approaches. IEEE Robotics & Automation Magazine, 13(4), 82–90.

[9] Zhang Shasha, Wang Zhouyu, Chen Lipeng, Mo Hao, Cui Yongjie. Multi-objective non-destructive picking path planning of kiwi fruit based on MatLab [J]. Agricultural mechanization Research, 2019, 41(04):18-23

[10] J. Lee, T. -W. Kim, S. Kang, K. Kim, J. Kim and J. B. Kim, Bin picking for the objects of non-Lambertian reflectance without using an explicit object model. 2014 11th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), Kuala Lumpur, Malaysia, 2014, 489-493.