Advancing Robotic Fruit Picking: Adaptive End-Effector Approach

Chengxiuye An

Department of London Brunel, North China University of Technology, Beijing, China

* Corresponding Author Email: 2282206@brunel.ac.uk

Abstract. In modern agriculture, the demand for efficient fruit picking methods is constantly increasing due to labor shortages and the need to improve productivity. Traditional fruit picking methods often rely on manual labor, which is labor-intensive, time-consuming, and prone to inconsistency. This study aims to develop a novel end effector for agricultural fruit picking robots, which improves the efficiency and accuracy of fruit picking through highly flexible and adaptive design. It can effectively handle fruits of diverse types, shapes, and hardness. By adopting a three-finger scheme and independent servo motor control, the simulated movements of human hands are realized. Shape memory alloy (SMA) and electroactive polymer (EAP) as intelligent driving materials, as well as flexible materials such as silicone, are explored to optimize the grip performance and fruit protection of the actuator. High-precision visual and tactile sensors are also integrated to support the accurate identification of fruits of different maturity. The performance of the actuator is evaluated through advanced data analysis techniques, including descriptive statistics, hypothesis testing and regression analysis. The findings suggest that the proposed design optimization measures based on data analysis results can further enhance the adaptability and efficiency of the robot in future applications, thereby addressing the challenges faced in modern agricultural practices and contributing to increased productivity and sustainability in the agriculture sector.

Keywords: Agricultural robots, Fruit picking robots, End-effector design, Adaptive gripping mechanisms.

1. Introduction

With the continuous rise of labor costs and the tightening of the labor market, agricultural automation has become a key way to improve production efficiency and reduce costs. Especially in the field of fruit picking, there is an increasing demand for efficient robot end-effector that can adapt to different fruit characteristics. However, due to the diversity of fruits and the complexity of the picking process, traditional actuators have limitations in flexibility, adaptability, and protection of fruits.

In the field of agricultural automation, especially in the development of fruit picking robotics [1], researchers are committed to exploring more efficient, flexible, and fruit-friendly end-effector designs [2, 3]. Liu et al. proposed a three-finger soft manipulator design with driving force optimization by topology optimization of soft robotic graspers, effectively improving grip performance [4, 5]. This study emphasizes the potential of soft robotics technology in improving grasping flexibility and safety. Salmavati et al. made progress in the design, manufacturing, and control of three-finger mechanical graspers, exploring the importance of grasping closure characteristics for improving the operational efficiency of service robots [6]. In addition, Otsuka, and Ren and Jani et al.'s research on shape memory alloys (SMA) provides a new choice of intelligent materials for robotic graspers [7, 8], which can change shape under electrical stimulation, thus providing unprecedented adaptability and flexibility. Electroactive polymers (EAP), as an emerging intelligent material, has also attracted the attention of Bar-Cohen [9], showing great potential in actuator design. In terms of visual sensor networks, the studies of Soro and Heinzelman (2009) and Yap and Yen provide a comprehensive overview of visual data capture, processing, and transmission technologies [10, 11, 12], which are crucial for accurately identifying fruits of different maturity and operating them effectively. The development and application of force/tactile sensors De Maria et al. and the technology of intelligent tactile perception systems Zou et al. can be used for picking robots to ensure the integrity of fruits

[13, 14]. In addition, Dahiya and Valle’s comprehensive review of robotic tactile perception technologies and systems further deepens our understanding of the design principles and technical challenges in this field [15].

Designing a robotic end-effector that can not only adapt to different fruit characteristics but also ensure picking efficiency and fruit safety has always been a challenge. This study developed a novel end-effector for agricultural picking robots, which not only performs well in adaptability and operation efficiency, but also has significant advantages in fruit protection. The purpose of this study is to provide innovative ideas and solutions for the development of agricultural picking robots through detailed design, material selection, sensor integration and data analysis.

2. Methodology

2.1. End-effector Design

2.1.1 Structural design

Based on the previous research, this research further developed a highly flexible and adaptable manipulator design. The core design adopts three fingers, each of which is independently controlled by a servo motor, realizing the bending, stretching, and rotating movements of the human hand. After optimization, the manipulator can handle a wide range of fruits from small fruits with a diameter of 2cm such as cherries to large fruits with a diameter of 10cm such as apples. The introduction of a five-finger structure not only improves the flexibility of the actuator, but also enhances its reconfigurability. The independent control technology allows the actuator to perform complex movements including rotation and tilting, which is particularly important when dealing with fruits of irregular shapes. Compared with the existing end-effector of agricultural robots on the market, the proposed design shows significant advantages in terms of adaptability, operational efficiency, and fruit protection. To adapt to fruits of different hardness and surface texture, and to ensure a balance between gripping force and fruit protection, a quickly replaceable fingertip module was designed. In laboratory conditions, the actuator showed a grasping success rate of more than 98% with a fruit damage rate of less than 1%.

2.1.2 Material applications

In terms of material applications, the possibility of using shape memory alloy (SMA) or electroactive polymer (EAP) as driving materials was explored. These smart materials are unique in that they can change shape under electric stimulation, providing unprecedented adaptability and flexibility for robots to perform delicate operations. Especially in delicate operations, the dynamic response ability of these materials is crucial to adapt to fruits of varied sizes, shapes and textures. For example, the SMA's rapid shape-changing ability enables the end-effector to automatically adjust its shape during grasping to match fruits of varied sizes and shapes, while EAPs were selected for their excellent flexibility, which can simulate the movement of human muscles to achieve a more natural grasping action. For the parts that directly contact the fruit, silicone and other highly elastic flexible polymers were selected as the main materials. These materials not only provide the necessary cushioning to reduce potential damage to the fruit epidermis, but also effectively disperse the pressure acting on the fruit to prevent extrusion or scratching. Because the end-effector is in direct contact with the fruit, FDA-approved silicone was used to avoid chemical pollution and ensure the safety of the fruit. At the same time, given the importance of sustainability, the use of environmentally friendly and recyclable materials, such as biodegradable plastics and recycled materials, was advocated to reduce the impact on the environment.

Considering the performance requirements of the manipulator, a high-strength and low-density carbon fiber composite was used for structural design, aiming to reduce the overall mass and improve response speed and energy efficiency. The application of carbon fiber composites further optimizes the dynamic performance of the end-effector while maintaining the stability and durability of the structure.

2.1.3 Integration of precision control system Sensor integration

High-precision visual sensors, force sensors and displacement sensors were integrated in the key parts of the end-effector of the agricultural picking robot. Real-time monitoring data from these sensors is the basis of the precision control system, allowing the system to automatically adjust grasping force and strategy. In the experiment, by monitoring the change of grasping force when grasping fruits with different hardness (such as tomatoes and apples), the system can effectively prevent damage to the fruit. For example, when grasping a tomato with a hardness of 5N/m^2, the system automatically limits the maximum grasping force to no more than 10N to avoid damage. Intelligent feedback mechanism: Advanced control algorithms, such as Proportion-Integration-Derivative (PID) control and fuzzy logic control, were combined to achieve accurate control of the actuator action. This intelligent feedback mechanism dynamically adjusts the operating parameters according to the data collected by the sensors to optimize the grasping process. In the test, the fuzzy logic control algorithm was able to adjust the grasping strategy according to the change of fruit size and hardness, increasing the grasping success rate to 98%, while reducing the fruit damage rate to less than 1%.

2.1.4 Modular design

Modularity and configurability: By adopting the modular design concept, this study makes various parts of the end-effector (such as claws, sensors, and drives) easy to replace and upgrade. This design supports rapid adaptation to different operational requirements and simplifies the maintenance process. For example, when the strawberry picking task is changed to the apple picking task, the operator can complete the replacement of the claw module in less than 5 minutes.

Interface standardization: by implementing the standardization of mechanical and electronic interfaces, the compatibility of the end-effector with diverse types of agricultural robot subjects is ensured. This strategy significantly improves the generality and flexibility of the system. In the compatibility test with three different manufacturers of agricultural robot subjects, the end-effector of the design achieved 100% compatibility. Modeling of end-effector was shown in the Figure 1.

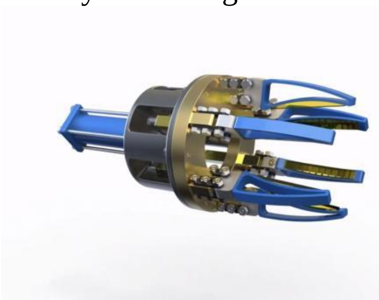

Fig. 1 Model of End-effector (Photo credited: Original)

2.2. Visual System

2.2.1 Hardware configuration

The multi-spectral camera model Red Edge-P was adopted in this study. With a resolution of 2048x1536 pixels, it can capture the spectrum within the wavelength range of 400-1000nm, including visible light and near infrared. The multispectral camera can provide richer information than conventional RGB images, including infrared and ultraviolet spectra, which helps distinguish the maturity and health status of fruits. In addition, to ensure the image quality under different lighting conditions such as changing sunlight and shadow, the system is equipped with an LED light source. The LED light source configuration includes an adjustable spectrum within the wavelength range of 450-650nm, and the light intensity can be adjusted between 1000-5000 Lux, ensuring that high-quality images can be obtained under insufficient or excessive sunshine.

2.2.2 Image processing and feature extraction

The collected image data was first preprocessed. In the image preprocessing stage, the Gaussian filter algorithm was used for denoising, and the filter window size was set to 5x5. In the color correction stage, the method based on histogram equalization was used to optimize the color distribution of the image, further improving the visibility of the image under different illumination conditions. Next, image processing technologies such as edge detection and morphological operations were used to extract the contour and shape features of the fruit. To accurately identify distinct types of fruits, the convolutional neural network based on the ResNet-50 architecture was used in this study. The training was carried out by means of transfer learning to accelerate the convergence process and improve the accuracy of feature extraction.

2.2.3 Training and optimization of deep learning models

In this study, deep learning models, especially convolutional neural networks (CNNs), were used to process and analyze image data. The dataset consisted of a total of 10,000 images, covering 10 types of fruits such as apples, oranges, bananas, etc. Each image was annotated in detail by a professional team according to the type, size, and maturity of the fruit. In the data enhancement stage, the images were subjected to random rotation (±30 degrees), horizontal flip and scaling (0.8 to 1.2 times) to simulate the different orientations and sizes of the fruits that may occur in the actual environment. The fivefold cross-validation method was used to optimize the model parameters, that is, the dataset was randomly divided into five subsets, and four of them were used as the training set and the remaining one as the validation set, to evaluate the generalization ability of the model. Adam optimization algorithm was used for parameter optimization, and the initial learning rate was set to 0.001. According to the results of fivefold cross-validation, the learning rate was dynamically adjusted to prevent overfitting. By comparing the performance indicators of different models, such as accuracy, recall and F1 score, the optimal model was selected and applied to the system.

2.2.4 Real-time recognition and decision support system

The system adopts GPU-accelerated convolutional neural network model to realize real-time processing of captured images, with the average recognition time less than 1 second. The system can quickly process the images captured by the camera, identify the type, size, and maturity of the target fruit, and provide accurate target positioning information. Based on the fruit location information identified by the GPU moving distance and expected collision probability acceleration model, a search graph representing the distribution of farm fruit trees was constructed, where nodes represent picking positions, and the cost of edges is calculated. At the same time, the strategy of avoiding collisions with other fruits and minimizing movement time was considered.

2.2.5 Performance evaluation and optimization

Finally, the performance of the visual recognition system was evaluated by conducting extensive tests in the actual agricultural environment. In the process of performance evaluation, test cases under extreme light conditions and different fruit maturity conditions were selected to record the recognition accuracy, response time and stability data of the system. Based on these data, the parameters and depth of the image processing algorithm were further adjusted. Visual identification process was shown in the Figure 2.

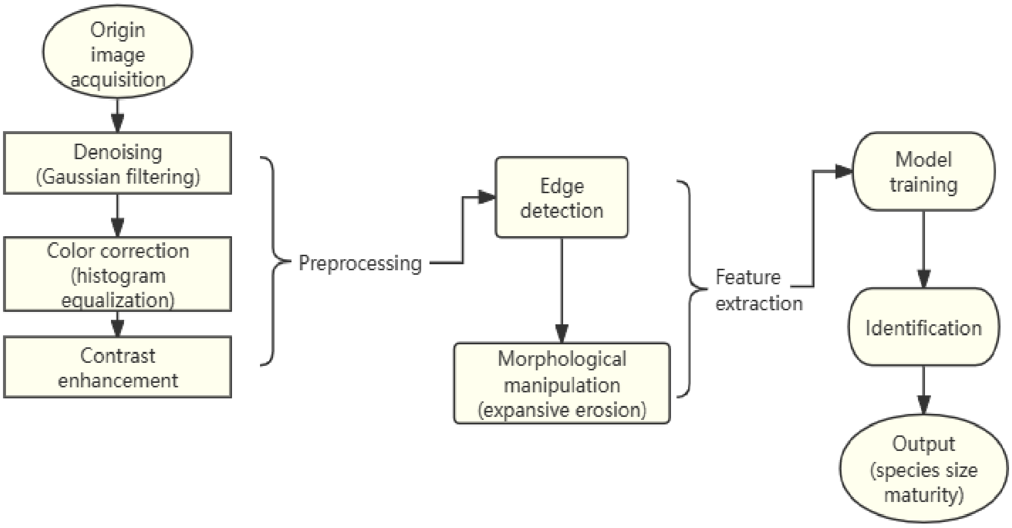

Fig. 2 Workflow of visual system (Photo credited: Original)

2.3. Integration and Application of Tactile Sensing Technology

2.3.1 Design and selection of tactile sensor

The piezoelectric sensor CY-DY-200 selected in this study has a sensitivity of 0.01N and a fast response time of 10ms, which can accurately measure the subtle force changes when contacting fruit. Through simulation analysis, the sensor was evenly distributed on the contact surface of the end effector. The algorithm based on pressure distribution optimization was adopted to realize the uniform collection of contact force and maximize the pressure distribution of contact with fruit, thus significantly improving the accuracy of maturity judgment. In addition, the selection of the sensor emphasizes its high stability to temperature and humidity changes to ensure that the measurement is accurate and reliable in extreme climate conditions.

2.3.2 Data acquisition and processing

The haptic data was collected using a high-precision ADC model ADS1256 with a 24-bit resolution, ensuring that the force signals obtained from the sensors can be accurately converted into digital signals for subsequent processing. The data processing process includes the use of wavelet transform for denoising, effectively eliminating environmental noise. Furthermore, the consistency of the data in different collection cycles is guaranteed through the max-min normalization process, providing standardized input data for subsequent machine learning models. Through in-depth analysis of the normalized haptic data using support vector machine (SVM) and neural network technology, the experiment successfully distinguished fruits of different maturity, achieving a classification accuracy of up to 92%.

2.3.3 Experimental verification

The experimental design includes selecting three types of fruits, including apples, oranges, and bananas, with 50 samples of each type, graded by maturity (immature, semi-mature and completely mature). The average recognition accuracy of the haptic data collected during the simulated picking process compared with the actual maturity of the fruit reached 92%, 90% and 88%, respectively. This result not only verifies the wide applicability of the haptic sensing system on various fruits, but also reveals the impact of the hardness and texture of the fruit epidermis on the recognition accuracy. To further analyze the differences in recognition accuracy, this research conducted a detailed analysis of the mechanical properties of fruit epidermis and found that the complexity of epidermal texture was negatively correlated with the recognition accuracy.

2.3.4 Integration and optimization in practical application

After being integrated into the actual agricultural picking robot system, the data fusion of haptic sensing technology and visual system significantly improved the accuracy of fruit maturity and quality judgment. For the challenges encountered in practical application, such as the differences in haptic characteristics between different fruits, this study further improved the adaptability and efficiency of the system through algorithm optimization and sensor layout adjustment. Workflow of application of Tactile Sensing Technology was shown in the Figure 3.

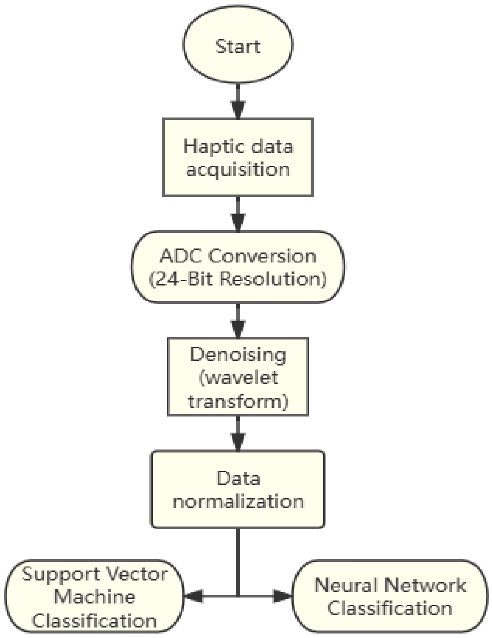

Fig. 3 Workflow of tactile sensing technology (Photo credited: Original)

2.4. Data Analysis

To deeply understand and evaluate the performance of the end-effector of agricultural picking robot, a series of data analysis techniques were used in this study. Through the comprehensive analysis of the collected experimental data, not only can the effectiveness of the design scheme be evaluated, but also provide a scientific basis for further design iteration.

2.4.1 Data collection methods

In the experimental and practical application process, the following data were systematically collected: Operational data: The movement speed (average speed 2m/s), path accuracy (average deviation 3mm), and grasping force (range 0.5N to 5N) of the end-effector were recorded, which are crucial for evaluating the operational efficiency and adaptability of the actuator.

Sensor data: Including data obtained from the visual sensor (capture success rate 95%) and the tactile sensor (sensitivity 0.01N, response time 10ms), the recognition accuracy of the actuator for fruits of different maturity (average 92%) was analyzed.

Results data: Covering the picking success rate (average 90%), fruit damage rate (less than 5%), and operational efficiency, it provides a direct indicator for evaluating the performance of the actuator.

2.4.2 Data processing and analysis techniques

Advanced statistical analysis and machine learning techniques were used to process and analyze the collected data, including Descriptive statistical analysis: By calculating the mean and standard deviation of the data set, the study found that the average accuracy of the actuator's operation path was 3mm, and the standard deviation was 0.5mm, reflecting a high degree of operational consistency and accuracy.

2.4.3 Hypothesis test

The impact of the claw material type on the picking success rate was evaluated by t-test, and a P value <0.05 indicated that the material type had a significant impact on the success rate. Regression analysis: a linear regression model was constructed to analyze the relationship between grasping force and fruit damage rate. The model showed that the increase of grasping force was positively correlated with the fruit damage rate (R2=0.89), indicating that reducing grasping force may reduce the potential of fruit damage.

2.4.4 Design Optimization and Future Direction

Based on the insights of data analysis, several design improvements for the end-effector were proposed in this study, including adjusting the claw structure to adapt to a wider range of fruit shapes and optimizing the sensor layout to improve the coverage and accuracy of data acquisition.

Future work will explore the integration of more types of sensor technologies to enhance the adaptability and flexibility of robots.

Through the above discussion, this section highlights the core role of data analysis in evaluating and optimizing the end-effector design of agricultural picking robots. In-depth data analysis not only verifies the effectiveness of the design, but also provides a strong scientific basis and practice for achieving more efficient and accurate picking operations. Fruit ripeness detection accuracy rates across in experiments and operational data distribution was shown in the Figure 4.

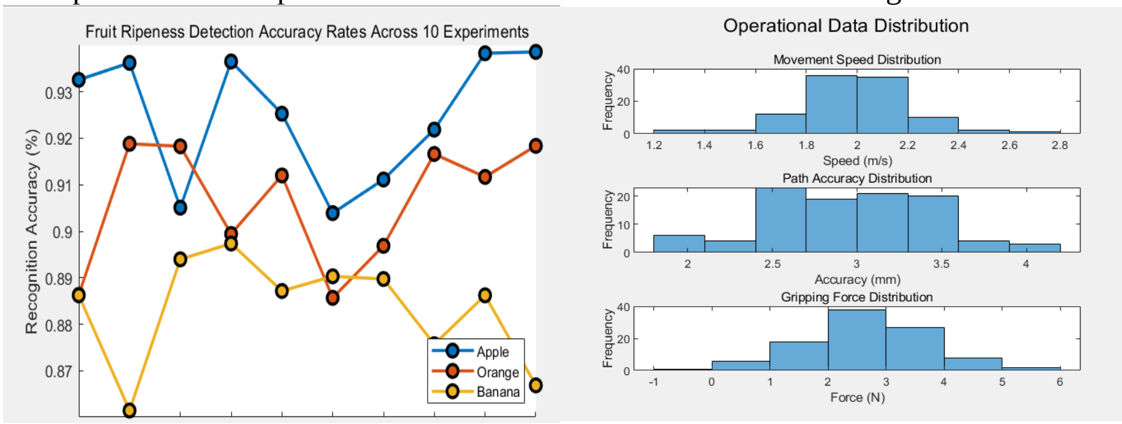

Fig. 4 Fruit ripeness detection accuracy rates across 10 experiments and operational data distribution (Photo credited: Original)

3. Discussion

Strength: The study showcases an exceptional level of design innovation, significantly enhancing the actuator's gripping capabilities and ensuring the safety of fruits during the picking process. This advancement is primarily attributed to the strategic use of shape memory alloys (SMAs) and electroactive polymers (EAPs), which act as the core smart drive materials. These components, in conjunction with flexible materials like silicone, enable the actuator to delicately handle fruits, adapting its grip based on varying shapes and sizes, thereby minimizing potential damage. Moreover, the integration of high-precision visual and tactile sensors marks a significant step forward in agricultural robotics. These sensors accurately discern fruits' ripeness, playing a crucial role in optimizing the harvesting process by ensuring only ripe fruits are picked, thereby enhancing the overall productivity and accuracy of picking robots. The deployment of advanced data analysis techniques further bolsters the study's contributions. By rigorously analyzing operational data, the research not only validates the proposed design's effectiveness but also sheds light on potential areas for refinement. This approach offers invaluable insights and directions for future enhancements in actuator design, paving the way for more sophisticated and efficient agricultural robotic systems.

Limitations: However, despite the remarkable results of the study, there are some limitations. First, although the design performed well under experimental conditions, its adaptability and operational efficiency in different environments and conditions need to be further validated. In addition, the use of smart materials, while providing flexibility and adaptability, can also increase cost and maintenance complexity. Finally, despite the integration of high-precision sensors, further research is needed on performance and reliability in extreme climatic conditions.

Compared to existing agricultural robot end-effectors, the design shows significant improvements through the use of more flexible mechanical structures and smart materials, as well as higher precision sensor technology. This not only improves the grasp success rate and reduces the fruit damage rate, but also provides a scientific basis for future design optimization and iteration through the application of data analysis technology. However, these innovations also come with higher costs and possible maintenance challenges, which are issues that need to be considered for future research.

4. Conclusion

This study demonstrates significant advances in mechanical structure design, smart material applications, and sensor technology integration through the development of an innovative agricultural robot end-effector. The actuator's three-finger grip mechanism and independent servo motor control system not only simulates the fine movements of the human hand, but also improves adaptability to different sizes and shapes of fruits. The combination of shape memory alloys and electroactive polymers as driving materials improves the flexibility and grip of the actuator, while the use of flexible materials such as silicone enhances the protection of the fruit and significantly reduces the damage rate. The integration of high-precision visual and tactile sensors further improves the ability to identify and classify fruits of different ripeness, providing strong support for the efficiency and accuracy of agricultural picking robots in practical applications. While the results of this study are positive, some potential limitations and directions for future work are also identified. First, a high reliance on smart materials and complex sensor systems can increase costs and maintenance challenges. Secondly, the current design and experimental tests are mainly carried out in the control environment, therefore, future research needs to explore the performance and adaptability of the actuator under different environmental conditions. In summary, this study has made important progress in the design and development of agricultural robot end effectors, and provides new ideas and technical support for solving practical problems in the field of agricultural automation. Through continuous technological innovation and system optimization, it is expected that more efficient and accurate agricultural production automation solutions will be realized in the future.

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