

Soft autonomous mobile manipulators in agricultural automation – a review

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Abstract

Purpose – This review paper aims to illustrate the potential of soft autonomous mobile manipulators (SAMM) in agriculture tasks involving harvesting and crop monitoring.

Design/methodology/approach – This paper systematically analyzes the major components involved: soft grippers, actuation and control methods, localization and path planning of mobile robots and integrated motion planning of mobile manipulators in agricultural environments.

Findings – While mobile robots and soft manipulators show promising individual developments, their integration faces significant challenges. Critical issues include real-time control implementation, environmental adaptability and coordinated task execution between mobility and manipulation systems.

Originality/value – This study addresses a significant gap in the literature, as there is currently no comprehensive review examining soft mobile manipulation systems and their integration into agricultural applications. By providing an in-depth analysis of core components, planning strategies and applications that combine delicate manipulation with efficient navigation, this work is a reference for researchers and practitioners developing state-of-the-art agricultural robotics.

Keywords Mobile manipulators, Path-planning, Harvesting robots, Agricultural robotics, Soft robotics, Soft grippers, Manipulation

Paper type General review

1. Introduction

The global agricultural sector faces mounting challenges requiring innovative solutions. Urbanization has caused labor shortages, affecting productivity, necessitating automated alternatives. Environmental concerns with conventional practices – particularly pesticides – pose risks to health and ecosystems. Farmers must increase production while reducing costs and environmental impact. Robotics offers precision, efficiency and sustainability in agricultural operations. Soft robotics and artificial intelligence advances enable machines to perform environmental monitoring, crop handling and precision farming (Amin *et al.*, 2023), reducing manual labor, minimizing errors and optimizing resource usage.

Industry 5.0 integrates human-centric and sustainable technologies through soft robotic manipulators and autonomous mobile robots (AMRs). Soft grippers with pneumatic and vacuum systems have revolutionized harvesting, weeding and planting delicate vegetation (Fu *et al.*, 2024). End-effectors have evolved from rigid designs (Elfferich *et al.*, 2024) to multi-finger, sensor-integrated systems (Ji *et al.*, 2024), improving collision avoidance, grip precision and adaptability.

AMRs transform farm management through sophisticated navigation and autonomy features. These systems use path-planning algorithms ranging from A** (Wang *et al.*, 2024d), Dijkstra's algorithm and rapidly-exploring random tree (RRT) to advanced machine learning methods. Deep reinforcement learning (Wang *et al.*, 2023c) enhances robots' navigation in complex agricultural environments, enabling adaptation to dynamic conditions. A key development has been adapting simultaneous localization and mapping (SLAM) to agricultural settings. Visual SLAM (V-SLAM) using depth and monocular cameras (Shu *et al.*, 2020), initially for indoor environments, has been modified for outdoor scenarios, addressing challenges of varying lighting and uneven terrain.

The convergence of soft manipulators and autonomous navigation into unified systems, known as soft autonomous mobile manipulators (SAMMs), represents the next frontier in agricultural automation (Yuan *et al.*, 2022). These systems integrate three key components: a manipulator arm, an intelligent mobile base and an adaptive soft end-effector. As shown in Figure 1, the SAMM architecture combines these elements into a versatile platform capable of navigating crop rows, identifying ripe produce and executing precise manipulation tasks in unstructured farm environments. However, this integration introduces unique challenges, including real-time coordination between mobility and manipulation, dynamic balance control and the design of control architectures capable of managing multiple degrees of freedom (Guo *et al.*, 2024). Addressing these challenges

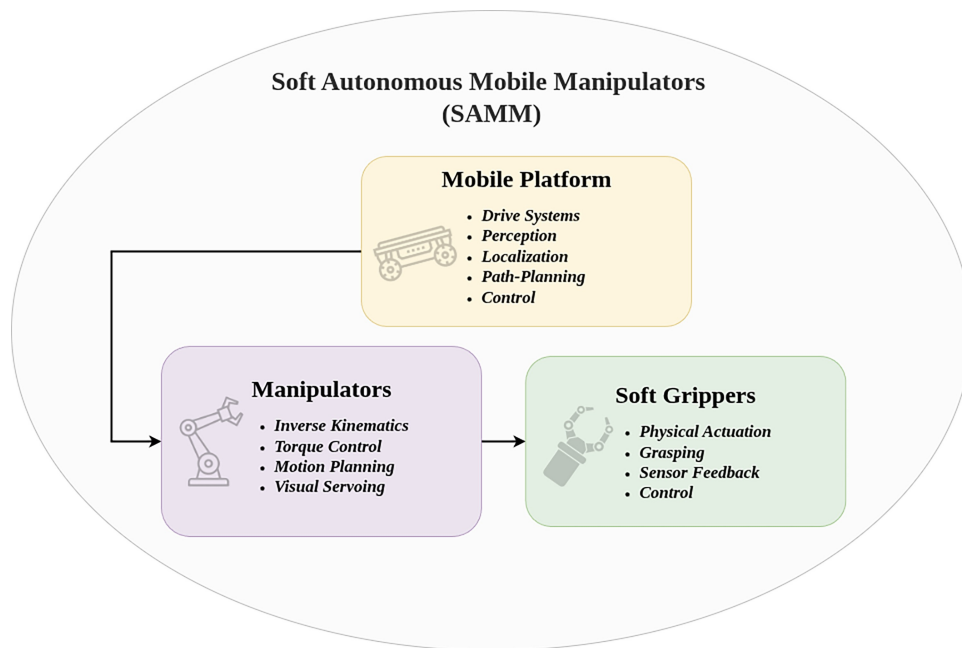
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Figure 1 Overview of a soft autonomous mobile manipulator (SAMM), comprising three integrated modules: a mobile robotic platform for navigation and localization, a manipulator arm for trajectory control and positioning and a soft gripper for compliant grasping



Source: Authors' own work

requires interdisciplinary advancements in hardware, software and systems engineering.

This review is structured into three sections corresponding to the components illustrated in [Figure 1](#):

- 1 Soft grippers in agricultural applications, covering design principles, actuation mechanisms and sensory systems.
- 2 AMRs, focusing on navigation strategies, path-planning algorithms and learning-based approaches.
- 3 System-level integration of manipulators with mobile platforms, highlighting current challenges, control architectures and future directions.

This review encompasses literature published between 2018 and 2025, selected through a systematic search process across multiple academic databases. Database Sources: IEEE Xplore, Google Scholar, ScienceDirect, Springer, Multidisciplinary Digital Publishing Institute, Wiley Online Library, Frontiers, arXiv and Social Science Research Network were systematically searched. Search strategy: a systematic three-phase approach was used to ensure comprehensive literature coverage:

- 1 *Soft robotics applications*: Primary keywords “soft grippers” OR “soft manipulators” were combined with “agricultural” OR “harvesting robots” to identify soft robotics applications in agriculture. Additional specific searches using “control” OR “soft sensors” combined with the previous keywords were conducted to capture papers focusing on actuation methods, sensors and control systems.
- 2 *Path planning and navigation*: The keyword “path planning” was combined with “mobile robot” AND (“agriculture” OR “harvesting”) to identify localization, path planning and drive systems literature. “Coverage path planning” was

specifically used to obtain highly relevant results for agricultural field operations.

- 3 *Mobile manipulator systems*: Papers were filtered from the above searches and supplemented with targeted searches using “mobile manipulator” combined with “agriculture” OR “harvesting” for comprehensive coverage.

To capture state-of-the-art navigation methods, “deep reinforcement learning” was additionally used in combination with previous keywords to get papers with an agricultural context. The systematic three-phase keyword approach across all nine databases initially yielded approximately 230 potentially relevant papers. Inclusion Criteria: Papers were retained if they demonstrated:

- direct application to agricultural or harvesting operations; and
- relevance to mobile manipulation, soft robotics or autonomous navigation in farming contexts.

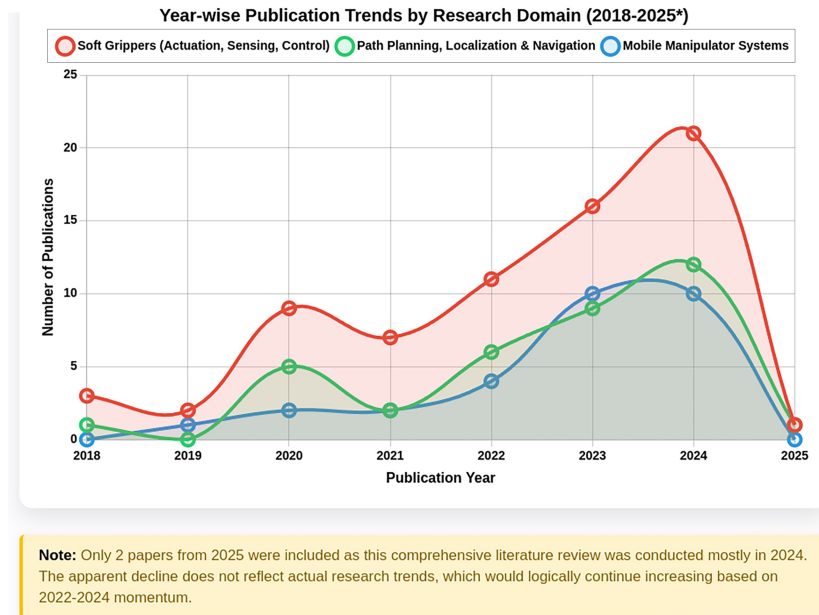
After screening, 126 high-quality papers were finally selected for comprehensive analysis, forming the foundation of this review. [Figure 2](#) presents the temporal distribution and domain analysis of the selected literature, illustrating the research trends and thematic categorization across the review period.

2. Soft grippers in agricultural automation

2.1 Traditional harvesting methods

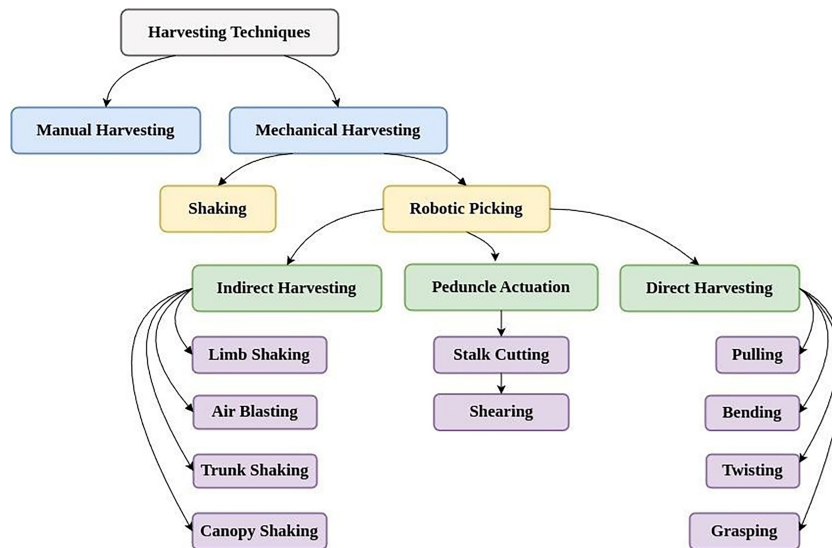
Fruit harvesting techniques are fundamental to robotic gripper design. [Figure 3](#) lists approaches used for harvesting. Traditional methods classify harvesting into mechanical and manual detachment, where mechanical methods use machines for fruit removal, while manual methods rely on human labor.

Figure 2 Year-wise subject domain trend analysis of chosen literature



Source: Authors' own work

Figure 3 Harvesting techniques classification



Source: Authors' own work

Mechanical harvesting subdivides into shaking methods and robotic picking for complete automation. A review by Navas *et al.* (2021b) proposed a classification system for robotic harvesting solutions. Building on previous frameworks, modern automatic harvesting methods are classified into three groups. First, indirect harvesting applies force to the plant rather than the fruit, using air blasting, limb shaking and trunk shaking techniques effective for crops like olives and pistachios. Second, direct harvesting applies mechanical force to the fruit or

peduncle, suited for strawberries, apples and tomatoes. Third, direct harvesting with peduncle actuation involves mechanical movement or cutting applied to the stalk, necessary for fruits with hard peduncles such as melons and peppers (Arad *et al.*, 2020). Appropriate harvesting method selection depends on tree size, structural fragility and fruit maturity. While indirect methods are primary for certain crops, these same crops can sometimes be harvested using direct contact techniques due to similar peduncle characteristics. Peduncle actuation methods

require sophisticated perception systems for detection and precise cutting without crop damage. Direct harvesting methods present challenges in robotic manipulation when replicating human harvesting movements. Picking patterns, including bending, lifting, twisting, grasping and pulling, have been studied.

Grasping and cutting mechanisms have emerged as significant methods, especially for crops like grapes (Vrochidou *et al.*, 2021). These systems require precise control to minimize damage. For tree crops, shaking systems have proven effective, where fruits dislodge through mechanical vibration and are collected using catching frames or net systems. Specifically developed for crops where vibration can dislodge fruit. Research on optimal harvesting techniques has been conducted for kiwis (Mu *et al.*, 2020) and strawberries. Peduncle actuation techniques require specialized cutting tools, classified by bending and shearing characteristics. Tool selection depends on specific peduncle properties and required cutting forces.

2.2 Classification and design principles

Soft grippers can be categorized based on a range of technical and operational parameters, as illustrated in Figure 4. Key classification dimensions include actuation methods (e.g. pneumatic, hydraulic, electric), grasping strategies and approaches (Cao *et al.*, 2023), detachment mechanisms, material composition, control architecture (open-loop vs closed-loop) and the operating environment (indoor or outdoor conditions). Their physical design varies from tentacle-like structures to anthropomorphic multi-fingered hands, tailored to accommodate different crop types and tasks. Many designs are inspired by biomimetic principles, drawing from natural organisms such as octopuses for dexterous manipulation (Song *et al.*, 2024) or twining plants for adaptive grasping (Cooper *et al.*, 2020). This classification aids in

understanding the suitability of different gripper architectures for specific agricultural scenarios.

3. Soft actuators

The evolution of agricultural robotics has led to significant advancements in soft actuation technologies, enabling gentle manipulation of agricultural produce. These developments offer unique advantages for specific farming applications as depicted in Table 1.

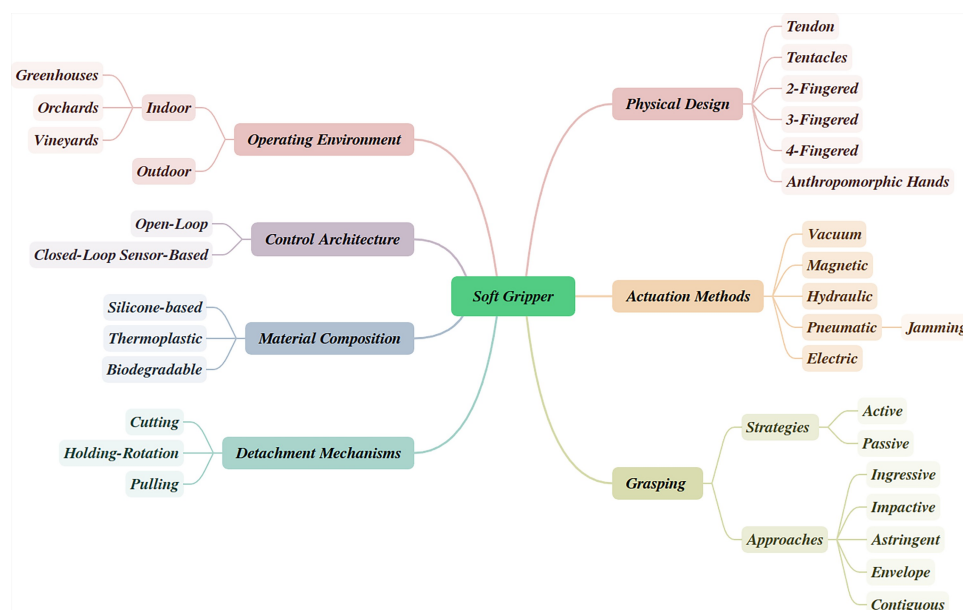
3.1 Pneumatic actuation

Soft pneumatic actuators (SPAs) operate through air pressure applied to internal chambers of deformable materials, causing bending and grasping. SPAs demonstrate flexibility with bending angles from 0° to 360°, providing extensive workspace. Manufactured using 3D printing, these actuators generate forces from 10 to 50 N. Pneumatic grippers are favored for high speed and low cost, minimizing bruising during handling. Multi-material 3D printing creates soft pneumatic grippers for irregularly shaped objects.

A notable example is the HortiBot, as shown in Figure 5(a), by Lenz *et al.* (2024), used UFactory xArm7 with a pneumatic four-finger soft gripper for sweet pepper harvesting. The PneuNet architecture by Manns *et al.* (2018), in Figure 5(b), features hollow chambers forming asymmetrical structures, generating controlled bending upon inflation.

The structure includes pneumatic channels of various sizes and shapes, with investigations into horizontal, vertical, rectangular and circular cross-sectional chambers optimized through finite-element methods. Single-channel actuators can bend toward the thicker wall side but may swell under high pressure. Twisting channels enable tentacle-like motions for

Figure 4 Classification of soft grippers based on key parameters, including actuation methods, physical design, grasping strategies, control architecture, material composition, detachment mechanisms and operating environment



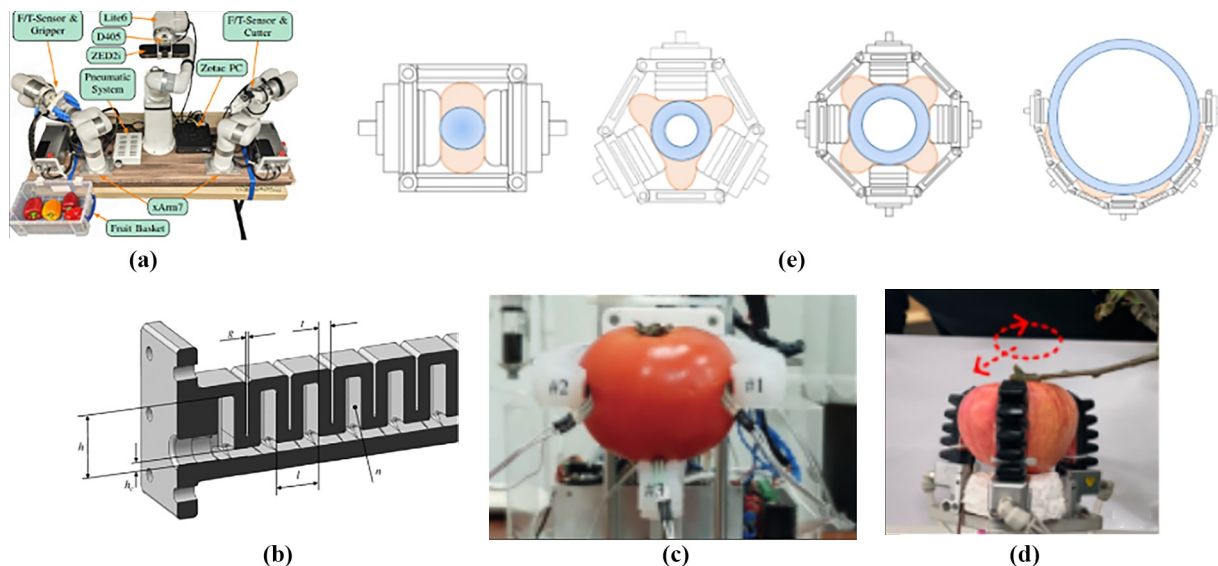
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Table 1 Overview of soft actuators in agricultural applications

Soft gripper description	Actuation method	Harvesting application	Performance metrics	Reference
Silica-gel coated telescopic	Pneumatic cylinders	Cherry tomato	Picking rate: 84%, Time: 6.4 s, Force: 16.4 N	Gao <i>et al.</i> (2022)
Dual-arm four-fingered	Pneumatic	Sweet pepper	Picking rate: 83.33%, time per fruit: 27 s	Lenz <i>et al.</i> (2024)
Tomato picking	Pneumatic cylinder	Tomato	Picking rate: 96.03%, time: 5 s	Ziwen <i>et al.</i> (2021)
Three-fingered [Figure 5(d)]	Pneumatic	Apple	Inner finger force: 8.52 N	Ji <i>et al.</i> (2024)
Silicone-based three-fingered	Pneumatic	Tomato	Maximum force: 2.57 N Handles 79–85 mm, 226–266 g fruits	Kultongkham <i>et al.</i> (2021)
Fiber reinforced diaphragm-based	Pneumatic	Strawberries, pumpkins and watermelon	Load capacity: up to 10 kg maximum force (hexagon): 54 N	Navas <i>et al.</i> (2021a)
Palm-shaped variable-stiffness	Jamming	Various fruits	Maximum gripping force: 19 N	Zhao and Wang (2023)
Composite fiber reinforced	Pneumatic	Eggs	Mean bending angle: 4.13 degrees	Yu <i>et al.</i> (2022)
Origami-shaped silicon suction	Vacuum	Cucumber	Success rate: 86.2%, damage rate: 4.7%	Jo <i>et al.</i> (2024)
Combined suction and cutting	Vacuum	Kiwi	Picking rate: 88%, Damage Rate: 7.3%	Fu <i>et al.</i> (2024)
Hybrid auxiliary fingered suction	Vacuum + pneumatic	Tomato	Picking rate: 70.1%, picking rate: 72.1%, Time: 14.6 s	Gao <i>et al.</i> (2024), Rong <i>et al.</i> (2022)
Three-fingered tendon-driven	Electric	Apple	Picking rate: 87.5%	Ninatanta <i>et al.</i> (2024)
Supercoiled polymer-based	Electric	Strawberry	Closed-loop control error: 2%, Response time: 3 s	Yang <i>et al.</i> (2020)
Magnetorheological	Magnetic	Eggs, strawberries, cherry tomatoes	Maximum holding force: 45 N	Choi <i>et al.</i> (2024)
Hybrid	Pneumatic + vacuum	Tomato	Suction grasping force: 12 N, pull-out force: 67.65 N at 140 KPa	Wang <i>et al.</i> (2023a)
Tendon-driven	Tendon	Blackberries	Picking rate: 95.24%, time: 4.8 s	Gunderman <i>et al.</i> (2022)

Source(s): Authors' own work

Figure 5 Pneumatic actuation (a) Horti bot, (b) PneuNets, (c) silicon pneumatic gripper, (d) three-fingered apple harvesting pneumatic gripper and (e) diaphragm-based pneumatic gripper



Source: (a) Lenz *et al.* (2024), (b) Manns *et al.* (2018), (c) Kultongkham *et al.* (2021), (d) Ji *et al.* (2024), (e) Navas, Fernández, Armada, *et al.* (2021a)

grasping small-radius objects. A study by [Kultongkham et al. \(2021\)](#), as shown in [Figure 5\(c\)](#), uses a three-fingered 3D printed SF820 silicone rubber pneumatic soft gripper operating within a 0–95 kPa pressure range, handling tomatoes 79–85 mm in diameter and 226–266 g in weight. A diaphragm-based design ([Navas et al., 2021a](#)), depicted in [Figure 5\(e\)](#), combines soft and rigid 3D-printed components using biodegradable polylactic acid (PLA), adapting between closed configurations for vertical fruits and open for ground fruits, handling produce from strawberries to watermelons by varying actuator numbers from two for small fruits to six in a U-shape for larger produce. The system achieves maximum loads of 10 kg in a hexagon-shaped configuration. While pneumatic-actuated systems offer advantages in cleanliness, safety and maintenance, they face challenges in position and speed control due to air compressibility.

3.1.1 Jamming

Jamming technology represents a specialized subset of pneumatic mechanisms enabling stiffness variation with minimal volume changes. While not strictly an actuation method, jamming can be activated under both positive and negative pressure. The technology includes three categories: granular, layer and fiber jamming, functioning as both primary gripper frameworks and stiffness variation mechanisms.

A palm-shaped variable-stiffness gripper ([Zhao and Wang, 2023](#)) using 3D-printed fabric jamming achieves 19 N maximum gripping force with minimal pushing force. These grippers have demonstrated effective grasping across diverse objects, including

mangoes, pitaya, grapes and apples ([Fang et al., 2022](#)), with their key advantage being the transition between flexible and stiffened states through geometric interlocking and frictional contacts. This adaptive capability provides both secure gripping and adjustable force for handling soft objects.

3.1.2 Fiber-reinforced soft actuators (FRSAs)

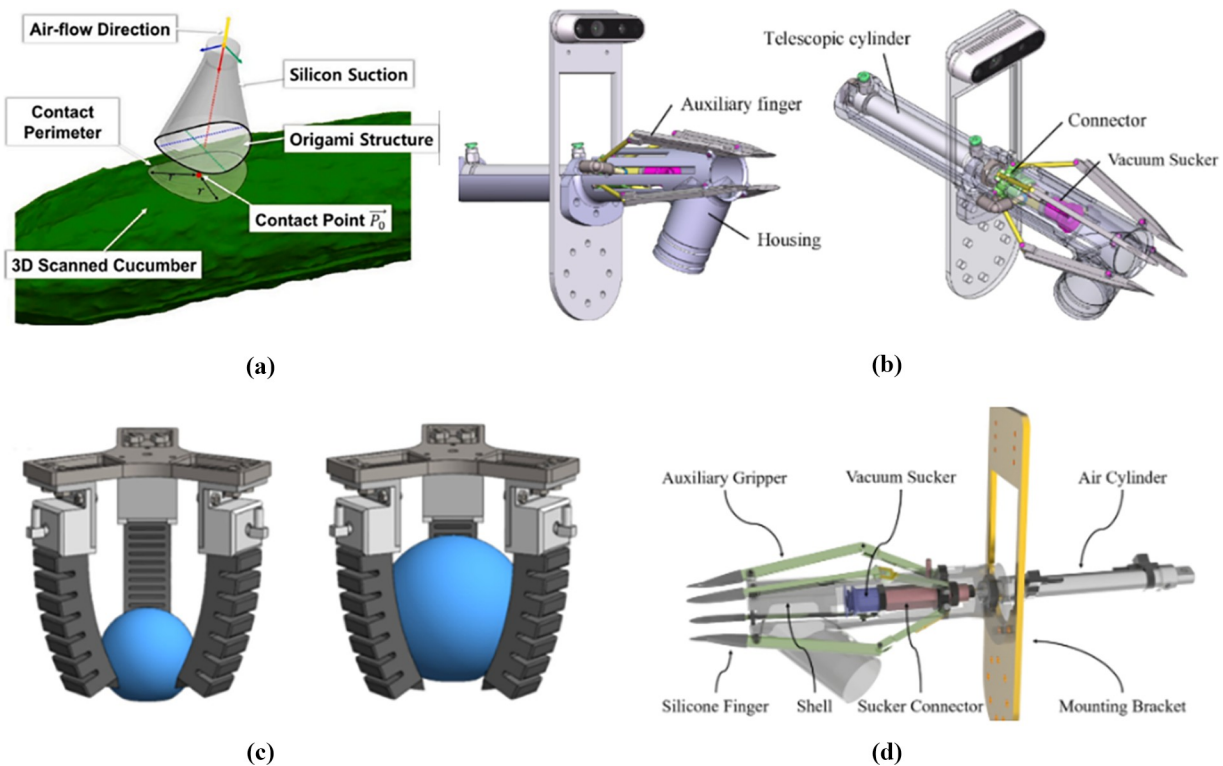
Fiber-reinforced soft actuators (FRSAs) ([Sun et al., 2022](#)) consist of elastomer actuators wrapped with inextensible reinforcements, operating through a single inflation channel, unlike traditional SPAs. Their programmable fiber orientation enables longitudinal extension, twisting ([Elfferich et al., 2024](#)) and bending while offering advantages in shape matching and higher force output.

FRSA grippers include rapid response capabilities through bistable laminates ([Zhang et al., 2022b](#)) and three-mode grasping systems. In agriculture, FRSAs have handled various produce from eggs ([Yu et al., 2022](#)) to pumpkins. Challenges in limited contact area and force control have been addressed through inextensible layer reinforcement ([Zhu et al., 2023](#)) and rigid component integration.

3.2 Vacuum actuation

Vacuum grippers use airflow to generate grasping force, suitable for non-rigid materials due to hygiene, low cost and control ease. These grippers handle various products, including mushrooms and tomatoes ([Jun et al., 2021](#)), using suction force. For cucumber harvesting ([Jo et al., 2024](#)), shown in [Figure 6\(a\)](#), developed a shape-adaptive suction cup gripper for

Figure 6 Vacuum actuation (a) shape-adaptive suction cup gripper, (b) hybrid actuation, (c) fingertip and envelope grasping and (d) auxiliary finger based hybrid actuation



Source: (a) [Jo et al. \(2024\)](#), (b) [Gao et al. \(2024\)](#), (c) [Zhuang et al. \(2023\)](#), (d) [Rong et al. \(2022\)](#)

curved surfaces, demonstrating an 86.2% success rate and a 4.7% damage rate across 174 trials, implementing a dual-arm system where one arm cuts the pedicel while the other grasps the fruit. [Fu et al. \(2024\)](#) used a soft gripper combining a suction cup with a precise cutter for kiwi harvesting, achieving 88.0% picking success and 7.3% damage rate through controlled negative pressure. Current research includes vacuum bending actuators (VBA) ([Katugampala et al., 2019](#)), enabling multi-plane motions for continuum manipulators along with innovative surfaces inspired by origami teeth and gecko-skin structures. Operation typically follows a sequence of fruit approach, vacuum activation, gripping through auxiliary fingers and controlled release.

3.3 Electrical actuation

Electric grippers use diverse actuation methods in agricultural robotics. For apple harvesting, a lightweight 3D-printed PLA gripper with thermoplastic polyurethane (TPU) skeleton ([Ninatanta et al., 2024](#)) achieved 87.5% success in apple capture at 0.33 m/s. [Yang et al. \(2020\)](#) introduced a supercoiled polymer (SCP) actuator in a Fin-Ray effect gripper, operating through Joule heating for voltage-controlled handling of delicate produce like strawberries.

3.4 Magnetic actuation

Magnetic actuation systems use magnetorheological (MR) fluid or magnetic materials for agricultural grasping. Developments include a porous magnetic soft gripper by [Li et al. \(2024a\)](#), combining high gripping force with compliance. A TPU design by [Choi et al. \(2024\)](#) achieved a 45 N maximum holding force, handling apples, strawberries, mushrooms and cherry tomatoes. While magnetic grippers offer advantages in compliance and secure gripping, challenges include MR fluid viscosity dependence and implementation costs.

3.5 Tendon actuation

Tendon-driven mechanisms operate through embedded tendons anchored within soft structures, enabling motions from basic inward bending to complex movements. These electric motor-driven systems provide precise force control, handling crops from blackberries ([Gunderman et al., 2022](#)) to heavier items like pumpkins and broccoli ([Lee et al., 2019](#)). Innovations include the Farm Hand with gecko-skin adhesives ([Ruotolo et al., 2021](#)) and combinations with pneumatics for high-speed operation ([Sun et al., 2022](#)) or layer jamming for enhanced grasping ([Fang et al., 2022](#)).

3.6 Hybrid actuation

Hybrid methods combine multiple actuation techniques; [Wang et al. \(2023a\)](#) integrated pneumatic actuation with vacuum manipulation using four tapered soft fingers and a suction cup, achieving 12 N suction force and 67.65 N pull-out force at 140 KPa. Comparable designs by [Gao et al. \(2024\)](#), shown in [Figure 6\(b\)](#), with auxiliary fingers have been explored for tomato harvesting, featuring a compact structure 314 mm in length, 80 mm in width and 120 mm in height, combining vacuum suction and pneumatic detachment. [Rong et al. \(2022\)](#), as shown in [Figure 6\(d\)](#), a similar design highlights limitations in the vacuum sucker's effectiveness on the tomato calyx. Additional developments include solenoid-activated

end-effectors with suction for tomatoes and pneumatically actuated soft cubic modules ([Tahir et al., 2018](#)). This method offers versatility through multiple operational modes and precise force control for delicate fruit harvesting.

4. Grasping

Robotic grasping presents a unique set of challenges in agricultural automation, particularly in the delicate task of harvesting fruits and vegetables. While seemingly straightforward, the complexity of robotic grasping in agricultural settings stems from the diverse shapes, sizes and fragility of produce, along with varying environmental conditions in fields and greenhouses. The success of robotic harvesting heavily depends on both the characteristics of the crop being handled and the sequence of operations involved in the harvesting process, from initial approach to final placement.

4.1 Grasping workflow

The agricultural robotic grasping process consists of a sophisticated sequence of coordinated operations, as detailed in [Zhang et al. \(2020\)](#). This multi-phase approach ensures optimal handling of delicate produce while maintaining high success rates and minimal damage.

The process begins with the approaching phase, where the robotic gripper carefully navigates toward the target produce using visual-servo systems to avoid obstacles like branches and leaves. This phase requires precise spatial awareness and real-time path planning to accommodate the dynamic agricultural environment. Once in position, the gripper initiates the contact phase, using force sensors to detect the slightest touch and prevent damage to delicate crops. This initial contact detection is critical for establishing the foundation of successful manipulation. Following initial contact, the system enters the force application stage, where precisely controlled pressure is gradually applied, carefully calibrated to account for the specific firmness and fragility of different crops. The pressure application must be adaptive, considering factors such as fruit ripeness, surface texture and structural integrity. The process continues as the gripper establishes a secure grip, applying optimal pressure that provides sufficient lifting force while avoiding any potential for bruising or damage. With the produce secured, the manipulation phase begins, involving careful detachment while maintaining steady force throughout to prevent drops or damage. This phase often requires coordinated movement patterns that accommodate the natural attachment points of fruits and vegetables. The final stages involve a controlled release, where the grip gradually loosens to place the produce gently into collection containers or transport systems. Throughout this entire sequence, sensors continuously monitor grip strength, tactile feedback and environmental factors to ensure optimal handling and make real-time adjustments as needed. This closed-loop control system enables the robotic system to adapt to variations in produce characteristics and environmental conditions dynamically.

4.2 Grasping strategies

An innovative development in agricultural robotics has been the “Holding-Rotation” strategy ([Tituaña et al., 2024](#)), specifically designed for delicate fruits. This method has shown remarkable success, achieving a 95.82% success rate with

cherry tomatoes (Zhang *et al.*, 2023b) and averaging just 4.86 s per pick. For strawberries, field tests demonstrated an impressive 94% success rate (Tituaña *et al.*, 2024). The strategy involves two key phases: a precise clamping stage where the correct force is applied to secure the fruit without damage, followed by a rotation stage where the gripper performs a calculated rotating motion to separate the fruit from its stem. The rotation motion is particularly effective because it mimics the natural harvesting motion used by human workers, applying torque at the stem attachment point where the fruit naturally separates with minimal force. The success of this strategy lies in its biomimetic approach, combining the precision of robotic control with the intuitive mechanics of manual harvesting. The clamping force is dynamically adjusted based on real-time feedback from tactile sensors, while the rotation parameters are optimized for different fruit types and ripeness levels.

Further research by Zhuang *et al.* (2023), as shown in Figure 6(c), compared fingertip and envelope grasping techniques. Envelope grasping demonstrated superior force generation, achieving 8.87 N at 60 KPa due to increased surface contact area. This technique involves wrapping the gripper around a larger portion of the fruit's surface, distributing forces more evenly and reducing the risk of pressure-point damage. The comparative study found that while smaller fruits like oranges can be successfully handled using fingertip grasping with 100% success rates, larger produce, such as apples and tomatoes, benefit from the enhanced contact force provided by envelope grasping. Fingertip grasping offers advantages in terms of precision and speed, making it ideal for delicate, small fruits where minimal contact is preferred. However, envelope grasping provides superior stability and force distribution for larger, heavier produce items. The choice between these techniques depends on several factors, including fruit size, weight, surface texture and fragility.

4.3 Slip detection

The integration of advanced slip detection systems represents a critical advancement in grasping, addressing fundamental challenges in delicate handling. Liu *et al.* (2024) developed a comprehensive slip detection framework using Tekscan's FlexiForce A201 pressure sensors and FLEX2.2" bend sensors integrated with Arduino Mega 2560 microcontrollers. The sensors, with their ultra-thin 0.008" profile and force sensing range up to 445 N, were strategically positioned on gripper fingertips to monitor contact forces, while FLEX2.2" sensors detected angular deflections up to 90° to monitor gripper deformation changes during slip events. The research extensively compared multiple signal processing techniques, including fast Fourier transform (FFT), high-pass filtering and wavelet transform analysis, with experimental results demonstrating that wavelet transform analysis significantly outperformed other methods, achieving detection accuracies of 94.2% compared to 78.3% for FFT analysis and 71.6% for high-pass filtering.

The system demonstrated real-time slip detection capabilities with response times under 50 ms, implementing a three-tier response strategy upon slip detection: immediate grip force adjustment (10%–15% increase), gripper repositioning if initial

adjustment proves insufficient and complete re-grasping for persistent slip conditions. Field testing with various agricultural produce demonstrated remarkable effectiveness, achieving a 97.3% success rate in preventing produce drops compared to 82.1% for systems without slip detection, while reducing bruising incidents by 78%. The system incorporated machine learning algorithms that continuously refined slip detection thresholds based on accumulated handling experience, reducing false positive detections by 65% over a 100-h operational period while maintaining high sensitivity to actual slip events. This comprehensive framework significantly enhances system reliability, providing consistent, damage-free harvesting operations while adapting to diverse field-based automation challenges.

5. Sensor technologies for soft grippers

In uncertain agricultural environments, closed-loop control becomes essential, relying on sensor systems for feedback on actuator deformation and environmental interaction.

5.1 Proprioceptive sensors

Proprioceptive sensors serve as fundamental components in soft grippers, focusing on activation status and intrinsic deformation such as bending or elongation. Commercial flex sensors (Chen *et al.*, 2018) measure bending angles and curvature, while Triboelectric sensors (Zhang *et al.*, 2022a) provide real-time tactile data. Stretchable strain gauges (Koivikko *et al.*, 2022) and embedded soft strain sensors (Park *et al.*, 2021) measure local strains and tip displacement. Pressure sensors monitor internal chamber pressure in SPA (Tawk *et al.*, 2021, 2022) for controlled grasping force.

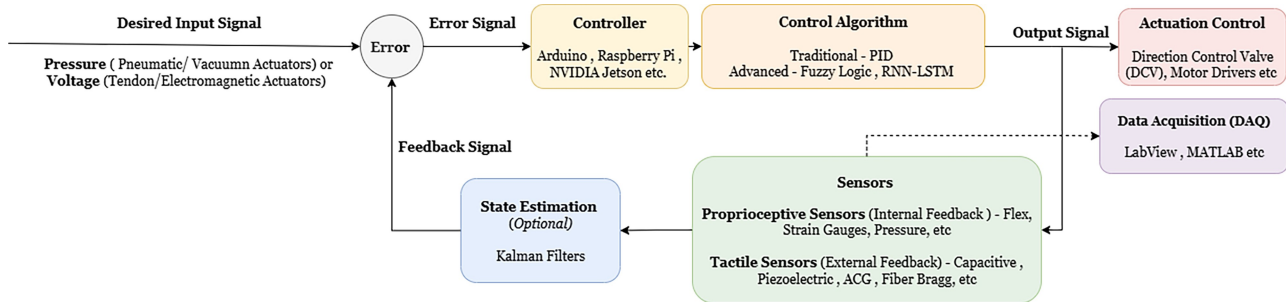
5.2 Tactile sensors

These sensors measure contact force, texture (Qu *et al.*, 2024b) and grasping success in three directions (Lu *et al.*, 2022). Notable developments include fiber Bragg grating sensors (Lai *et al.*, 2024) and electroactive polymer sensors (Briggs *et al.*, 2023) capable of detecting pressures as low as 0.005 N. Air gap-controlled (AGC) bimodal tactile sensors (Min *et al.*, 2023) detect pressure and bending strain simultaneously, achieving 98.78% classification accuracy in tomato handling via artificial neural network (ANN). Flexible strain sensors use conductive films with flexible substrates to measure resistance and capacitance changes under deformation (Konishi *et al.*, 2022). Polydimethylsiloxane-based capacitive sensors assess fruit ripeness (Maharshi *et al.*, 2022), while piezoelectric sensors show 17.82 MPa¹ sensitivity for fruit hardness (Xia *et al.*, 2022). These sensors enable constant-pressure feedback in apple harvesting systems (Chen *et al.*, 2022). Integrating proprioceptive, tactile and pressure sensors provides feedback for precise handling, accommodating varied soft gripper designs and actuation.

6. Control methods for soft gripper actuation

Soft grippers generally use either open-loop or closed-loop control strategies, as summarized in Figure 7, which presents a comprehensive block diagram of typical soft gripper control systems. In open-loop configurations common in pneumatic actuators, basic on/off actuation is performed via directional control valves. In contrast, closed-loop systems use real-time

Figure 7 Block diagram of a typical soft gripper control system showing integration of closed-loop architectures with controllers, actuators and sensors. Feedback from tactile and proprioceptive sensors enables real-time state estimation and adaptive control



Source: Authors' own work

feedback from internal (proprioceptive) and external (tactile) sensors to enhance precision, using techniques such as Kalman filtering for state estimation and neural networks for adaptive control.

6.1 Classical control systems

Traditional methods remain effective. Wang *et al.* (2024b) combined Kalman filtering with proportional-integral-derivative (PID) control, achieving 0.07 N steady-state error. Li *et al.* (2021) implemented an STM32-based incremental PID for accurate motor speed control in delicate fruit handling. Kultongkham *et al.* (2021) used a ten-sub-chamber design producing 1.62 N per finger. Fu *et al.* (2024) integrated infrared, photoelectric and Hall sensors for position monitoring. Microcontrollers like Arduino (Brown and Sukkarieh, 2021; Wang *et al.*, 2023a) and LabVIEW interfaces (Navas *et al.*, 2021a) are used for pneumatic control and PID-based pressure feedback.

6.2 Advanced control systems

George Thuruthel *et al.* (2022) used conductive thermoplastic elastomer (CTPE) with recurrent neural networks (RNNs) for nonlinear state estimation, achieving 0.17 ± 0.14 N average error at 25 Hz using long short-term memory networks. Averta *et al.* (2022) developed RNN-based systems predicting failure direction with 75% accuracy and 85% grasp success.

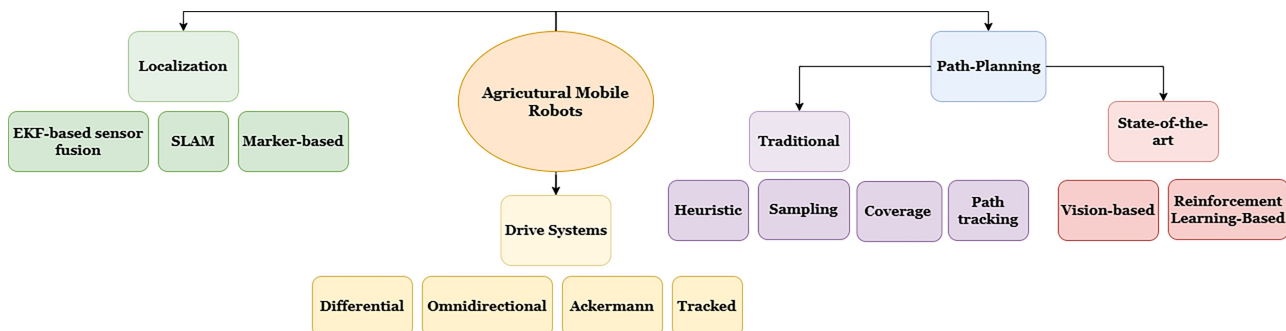
6.2.1 Current research and advancements

Flexible-fingered grippers show strong agricultural performance. A three-fingered design (Liu *et al.*, 2020) enables multi-orientation apple harvesting while minimizing damage (Ji *et al.*, 2024; Zhao *et al.*, 2023). Fluidic elastomer actuators (FEAs) offer low-cost fabrication and strong grip (Birrell *et al.*, 2020). FEA-tendon hybrids combine strengths of both, achieving a 7.06 payload-to-weight ratio. JAIST's ROSE gripper (Bui *et al.*, 2024) uses rotating dual-layer elastomer cups that wrinkle upon actuation, mimicking floral movements for adaptive grip on irregular produce like bell peppers. The inner layer rotates at 15 RPM, creating radial wrinkles that apply uniform pressure (0.8–1.2 kPa), reducing positional accuracy needs by 60% and tolerating ± 10 mm error. Similarly, Clark *et al.* (2025) created a Ninjaflex gripper with hair-like microstructures and electrostatic adhesion to better grip waxy fruit surfaces.

7. Autonomous mobile robots in agriculture

Mobile robots are revolutionizing agriculture through autonomous field navigation, integrating sensors and edge-computing systems for complex farming environments. As illustrated in Figure 8, agricultural mobile robots consist of three core components: drive systems, localization techniques and path-planning algorithms, discussed in detail in the following section.

Figure 8 Overview of key components in agricultural mobile robots, including drive systems, localization methods and path-planning algorithms (approaches)



Source: Authors' own work

7.1 Drive systems

Differential drive systems using independently driven wheels excel in precision tasks like weeding and crop monitoring (Iqbal *et al.*, 2020). Variants include four-wheel systems with spring-damper suspension for greenhouses (Wang *et al.*, 2024d) and skid-steer platforms for crop inspection (Monsalve *et al.*, 2022). Omnidirectional drives allow movement in any direction, demonstrated by screw-driven robots for forestry data collection (Yao *et al.*, 2025). The Ackermann drive system provides high-speed stability for row planting and harvesting (Mwitta and Rains, 2024) but requires larger headlands for turning. Tracked drive systems (Fu *et al.*, 2024; Wu *et al.*, 2024) are most widely used, distributing weight and enhancing traction on muddy or uneven terrain.

7.2 Localization techniques

Effective localization methods shown in Table 2 are based on sensor fusion, with extended Kalman filter (EKF) integrating data from global positioning systems (GPS), inertial measurement units (IMU) and wheel encoders. For instance, Mwitta and Rains (2024) implemented a ROS-based system with Kalman filtering on wheel encoder and IMU data, while Yan *et al.* (2022) used EKF to fuse wheel odometry with visual-inertial odometry (VIO) in GPS-denied settings, achieving exceptional precision of 2.27–14.12 cm root mean square error

(RMSE) across greenhouse environments with 75%–95% improvement over VIO alone. Wheel odometry proves effective in structured environments when paired with PID control (Monsalve *et al.*, 2022) but accumulates errors due to slippages.

SLAM offers dynamic mapping and localization using LiDAR and cameras, with Hector SLAM demonstrating robust waypoint navigation in greenhouses (Harik and Korsaeht, 2018) and 3D SLAM excelling in kiwi harvesting with real-time kinematic (RTK)-GPS providing centimeter-level accuracy (Fu *et al.*, 2024). LeGO-lidar-based odometry (LOAM) enables real-time large-scale mapping (Qu *et al.*, 2024a), achieving 5 cm indoor accuracy but degrading to 20.5 cm outdoors, while the adaptive fusion principal component pursuit (AF-PCP) algorithm (Tan *et al.*, 2024) achieved exceptional performance with 2.6–4.6 cm localization accuracy, 155.7% mapping area improvement and 79.9% error reduction. In orchards, Qin *et al.* (2024) combined scan context and normal distributions transform – iterative closest point, achieving 57 cm RMSE while outperforming lightweight and ground-optimized lidar odometry and mapping by 68%. Visual SLAM provides a cost-effective alternative, with ORB-SLAM3 achieving 24 cm to 169 cm RMSE depending on environmental complexity (Schmidt *et al.*, 2025), demonstrating significant variability across lighting and weather conditions in agricultural environments. Marker-based localization using AprilTags achieved exceptional precision with 8.57 cm MAE and

Table 2 Localization techniques used in agricultural mobile robots

Localization method	Sensors	Application	Accuracy	Strengths	Limitations	References
VIO-EKF based	GPS, IMU, encoders	Greenhouses	Very high	Robust sensor fusion, sub 15-cm RMSE	High computation	Yan <i>et al.</i> (2022)
Wheel odometry	Encoders	Indoor/outdoor	Moderate	Cost-effective, simple implementation	Wheel slippage, terrain variations	Monsalve <i>et al.</i> (2022)
Hector SLAM based	LiDAR, IMU	Greenhouses	High	Real-time robust mapping with 15 Hz rate up to 10 cycles	Success is measured via waypoint convergence rather than trajectory following	Harik and Korsaeht (2018)
3D SLAM	Depth camera, GPS LiDAR, IMU	Kiwi harvesting, orchards	Very high	Detailed 3D environmental data, multi-sensor robustness	High computational cost, GPS weather sensitivity	Fu <i>et al.</i> (2024)
LeGO-LOAM	GPS, LiDAR, IMU	Large agricultural fields	High	Robust LIDAR-based odometry, 5 cm average error	Accuracy degradation in outdoors (20.5 cm error), loop closure difficulty	Qu <i>et al.</i> (2024a)
AF-PCP	LiDAR, GPS	Orchards, large farms	Very high	Sub 5 cm (2.4–4.6 cm) localization accuracy, 155.7% increase in mapping area	High processing power, high-quality LiDAR (16 line) required	Tan <i>et al.</i> (2024)
Scan context + NDT-ICP	LiDAR, IMU	Orchards	Moderate	68% RMSE reduction compared to LeGO-LOAM	Moderate Absolute Accuracy 57 cm, long-term drift	QIN <i>et al.</i> (2024)
Visual SLAM (ORB-SLAM3)	RGB camera, IMU	Greenhouses	Moderate	Cost-effective alternative to a 3D LiDAR	Struggles with feature-poor areas, variable accuracy	Schmidt <i>et al.</i> (2025)
Marker-based localization	Monocular camera	Indoor	Very high	Precise tracking (9 cm error)	Requires predefined markers in the fields, limited scalability	Zhang <i>et al.</i> (2023a)

Source(s): Authors' own work

8.59 cm RMSE in greenhouses under dynamic lighting (Zhang *et al.*, 2023a), displaying effectiveness in indoor environments.

7.3 Path planning in agricultural environments

Path planning is essential for agricultural robots Table 3 performing tasks such as planting, harvesting and weeding. Deep learning techniques (Onishi *et al.*, 2019) facilitate real-time decision-making, while reinforcement learning introduces experiential improvements using reward feedback. Combining traditional and modern techniques has enhanced the robots' ability to navigate complex terrains and perform precise tasks.

7.3.1 Traditional path planning algorithms

The A* algorithm remains prominent for global path planning among traditional methods. Enhanced versions have achieved significant improvements in greenhouse orchards, reducing path turning points by 40% and overall path length by 4.63% (Chatzisavvas *et al.*, 2024) while achieving a 22.78% reduction in optimal path distance and an 80.65% decrease in search nodes in broader implementations (Fan *et al.*, 2024). Integrating model predictive control (MPC) has enabled dynamic trajectory replanning (Lu *et al.*, 2024), demonstrating precise navigation with a 39.7 cm maximum deviation at 0.4 m/s in orchards (Li *et al.*, 2024b).

The dynamic window approach (DWA) has proven effective for local planning by evaluating potential velocities within a dynamic window at each time step defined by robot kinematics and environmental conditions. The algorithm optimizes three key parameters: heading, obstacle distance and forward velocity. When integrated with GPS-based planning, it achieved lateral deviations averaging 9.5 cm during row following and 14.6 cm during end-of-row turns (Mwitta and Rains, 2024). Its fuzzy logic enhancement further improved performance with a 40% reduction in turning points and a 1.92 times increase in safety distance (Wang *et al.*, 2024d).

The artificial potential field (APF) algorithm treats robots as charged particles influenced by attractive and repulsive forces. These forces are continuously calculated in real time based on the robot's position, with the total guiding force computed as their sum (Mancini *et al.*, 2023). Its enhanced version, the artificial electric potential field method (AEPF) (Wei *et al.*, 2024), achieved 60 ms computation times in greenhouses, enabling efficient navigation

through tight spaces while dynamically avoiding obstacles such as plants, equipment and workers (Harik and Korsath, 2018).

Similarly, the RRT algorithm has evolved for agricultural applications. The environment-driven direction and dynamic step size bidirectional RRT (EDDS-bi-RRT) (Kang *et al.*, 2024a) improves upon the traditional approach by incorporating environmental information to optimize both expansion direction and step size, achieving an 89% success rate in apple harvesting with a 17-DOF humanoid dual-arm robot. The continuous bidirectional quick-RRT (CBQ-RRT), proposed by Ye *et al.* (2024) for orchard environments, enhances path smoothness and node expansion efficiency. It demonstrated precise navigation with a maximum lateral error of 0.334 m and an execution time of 1.68 s in strawberry harvesting scenarios. Coverage path planning (CPP) represents a specialized category that fundamentally differs from traditional navigation approaches. Unlike conventional point-to-point planning, CPP emphasizes complete workspace coverage, making it crucial for agricultural applications where robots must systematically cover entire fields or orchards. The implementation typically begins with creating a grid map model through UAV-acquired remote sensing images, followed by cell decomposition for systematic traversal. This approach often integrates with traditional algorithms like A* for optimizing paths between target points, considering factors such as turning velocities to minimize time costs. Formation-based algorithms by Chen *et al.* (2024a), shown in Figure 9(a), achieved coverage rates exceeding 98.1% with a minimal redundancy of 0.007%. The development of hybrid complete coverage path planning (CCPP) approaches, shown in Figure 9(d), combining inner spiral and nested methods, has further enhanced effectiveness with 97% coverage rates (Wang *et al.*, 2024b). The inner spiral technique initially covers field edges to create turning space, then plans a spiral path moving from the outside inward while maintaining consistent width between layers. For complex field shapes, specialized approaches, shown in Figure 9(b), combining Reeds–Shepp curve planning with shape-based algorithms, have demonstrated a 95.69% coverage rate, achieving an 18.3% improvement in coverage rate for arbitrary quadrilateral fields (Tituaña *et al.*, 2024).

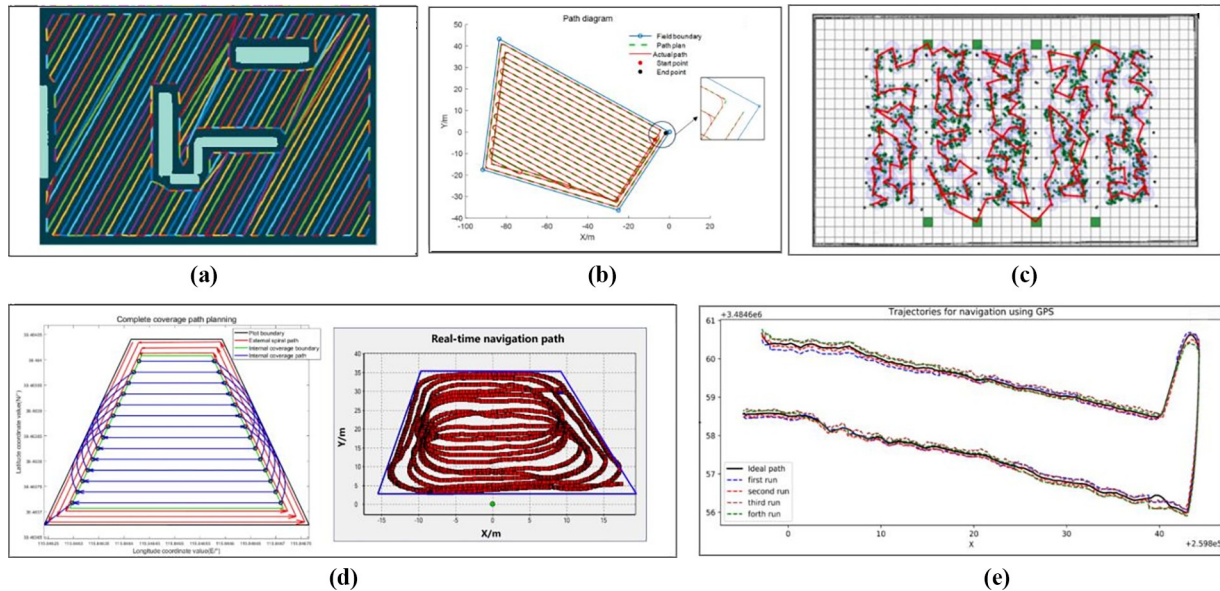
The pure pursuit algorithm, introduced in 1992, calculates curvature to reach a look-ahead point. Enhancements with dynamic look-ahead and GPS by Mwitta and Rains (2024), shown in Figure 9(e), have improved row navigation.

Table 3 Path planning in agricultural environments

Algorithm	Category	Application	Reference
EDDS-bi-RRT	Sampling	Apple harvesting	Kang <i>et al.</i> (2024b)
CBQ-RRT	Sampling	Strawberry harvesting	Ye <i>et al.</i> (2024)
APF	Potential field	High-density greenhouses	Mancini <i>et al.</i> (2023)
AEPF	Potential field	Field data collection	Wei <i>et al.</i> (2024)
DWA	Grid-based	Global planning in cotton fields	Mwitta and Rains (2024)
Fuzzy DWA	Grid-based	Dynamic obstacle avoidance	Wang <i>et al.</i> (2024d)
Coverage path planning (CPP)	Coverage-based	Precision agriculture, spraying, weeding	Chen <i>et al.</i> (2024a)
Hybrid CPP	Coverage-based	Greenhouse monitoring, spraying	Wang <i>et al.</i> (2024c)
Pure pursuit algorithm	Path tracking	Autonomous waypoint navigation	Mwitta and Rains (2024)
Deep reinforcement learning	Machine learning	Navigation for kiwifruit harvesting	Kang <i>et al.</i> (2024a)
CNN row detection	Vision-based	Paddy field navigation	Adhikari <i>et al.</i> (2020)
Hough transform	Vision-based	Orchard tree row detection and navigation	Adhikari <i>et al.</i> (2020), Nizam <i>et al.</i> (2024)

Source(s): Authors' own work

Figure 9 Coverage path-planning (a) formation-based, (b) Reeds–Shepp curve planning, (c) re-DQN-based coverage planning, (d) hybrid complete coverage path planning (CCPP) rates and (e) pure pursuit-based GPS-enhanced global planning



Source: (a) [Chen et al. \(2024a\)](#), (b) [Tituaña et al. \(2024\)](#), (c) [Wang et al. \(2023c\)](#), (d) [Wang et al. \(2024c\)](#), (e) [Mwitta and Rains \(2024\)](#)

OpenPlanner combines global and local planning with behavior states, using cost functions that account for terrain and vegetation ([Yao et al., 2024](#)).

7.3.2 State-of-the-art algorithms

Modern agricultural navigation increasingly uses machine learning. Deep reinforcement learning enables robots to learn optimal paths through environmental interaction, with a kiwifruit harvesting system, shown in [Figure 9\(c\)](#), reducing path length by 31.56% and time by 35.72% using re-DQN ([Wang et al., 2023c](#)). The ARAES framework ([Kang et al., 2024a](#)) uses the soft actor-critic (SAC) algorithm and a reward system based on distance, progress and safety, enabling navigation without prior maps. Vision-based methods use deep encoder-decoder networks for crop row detection in paddy fields through semantic graphics, implementing proportional control for navigation ([Adhikari et al., 2020](#)). In orchards ([Nizam et al., 2024](#)) used the Hough Transform for line detection, combining visual data with GPS and compass information for accurate trajectory control between tree rows

8. Mobile manipulators in agriculture

Mobile manipulators ([Ghodsian et al., 2023](#)) integrate a mobile base with a robotic arm, enabling autonomous navigation and precise manipulation in agricultural environments. Unlike stationary systems, they can traverse large, uneven fields and orchards while performing tasks such as harvesting, pruning and planting. To enhance maneuverability over challenging terrain, many agricultural mobile manipulators use tracked-drive systems ([Chen et al., 2024b](#)), which offer superior traction and stability for effective navigation through muddy fields, over obstacles and on sloped surfaces. Computer vision

methods, as explained in [Liu and Liu \(2023\)](#), enable accurate fruit localization and motion planning.

Recent developments have introduced more sophisticated configurations, like dual-arm manipulators, to improve efficiency. [Gong et al. \(2022\)](#) had explored their application in occluded tomato harvesting, leveraging depth cameras and extended Mask-region-based convolutional neural network (RCNN) algorithms. Similar approaches use Mask-RCNN with 3D point cloud segmentation. [Yi et al. \(2024\)](#) and GAN-based dual-arm systems for strawberry localization ([Wang et al., 2023b](#)). For specialized crops, a [Li et al. \(2023b\)](#) developed a tea-harvesting mobile manipulator featuring a 3P delta arm with a blade end-effector. This system addresses the challenges of harvesting small and delicate tea leaves by combining YOLOv3 detection with point cloud generation for precise localization, using principal component analysis to determine optimal plucking points and genetic algorithms for motion planning.

These systems have also been adapted for precision pollination, using neural networks like you only look once (YOLO)v5, YOLACT++ and DETR for accurate flower detection and pistil identification ([Yang et al., 2023](#)). In scenarios involving partially occluded fruits, deep convolutional neural networks combined with frustum-based point cloud methods have been used for efficient apple harvesting ([Li et al., 2023a](#)). A unique application is a mobile manipulator with a 3-DOF arm specifically designed for soil sensing and phenotyping applications ([Iqbal et al., 2020](#)). Combining mobility with manipulation capabilities makes them well-suited for precision agriculture.

8.1 Soft mobile manipulators

Soft grippers combined with mobile platforms enable gentle handling of delicate crops by conforming to irregular shapes

and applying appropriate force. As illustrated in Table 4, various implementations have shown impressive success rates: Vacuum-actuated grippers developed by Fu *et al.* (2024) for mushroom harvesting achieved 94.1% success, while soft-fingered apple harvesters reached 91% (Kang *et al.*, 2020), significantly broadening the range of viable crops for autonomous harvesting.

8.2 Motion planning for mobile manipulators

Motion planning for agricultural mobile manipulators is a multi-stage process that integrates perception, base navigation, manipulator control and gripper interaction. Figure 10 illustrates a comprehensive control architecture for such a system, segmented into four functional modules: perception, mobile base planning and control, manipulator planning and control and soft gripper control.

The pipeline begins with perception, where depth or stereo cameras capture images of the environment. A deep learning-based fruit detection module (e.g. YOLO, Mask R-CNN) identifies objects of interest such as ripe fruits. Subsequently, fruit pose estimation extracts the 3D pose (x , y , z) of each detected target, enabling precise manipulation. The mobile

base planning and control module is responsible for navigating the field to position the manipulator within operational range. Initially, global field planning uses GPS and pre-mapped or UAV-derived field data to generate a coverage path. State estimation (via Kalman filters) fuses data from LiDAR, encoders and IMUs for accurate odometry.

Furthermore, SLAM is used to localize the robot accurately. Using this information, local base planning techniques like DWA, APF or trajectory generation algorithms compute feasible paths considering local obstacles. The generated trajectories are then tracked by a trajectory tracking and control layer using control strategies such as MPC or pure pursuit algorithm.

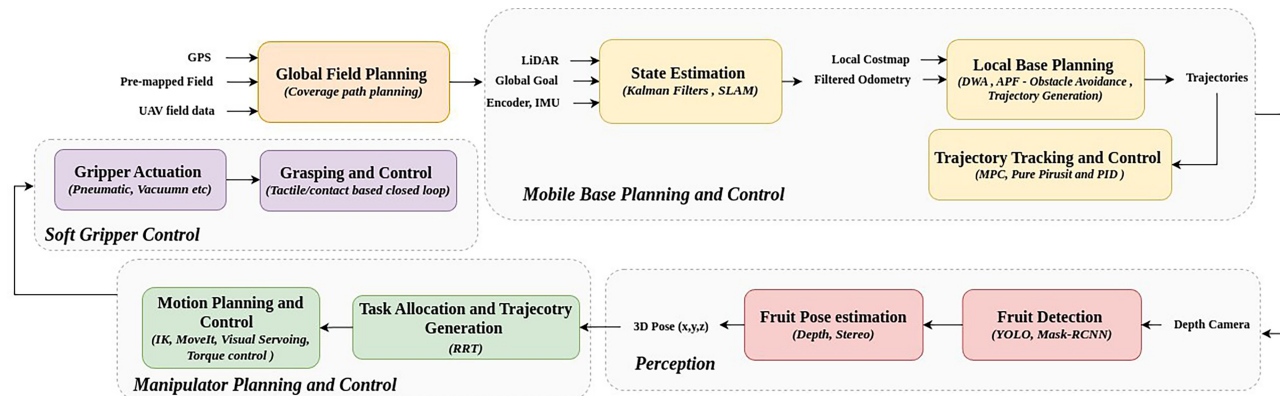
Once the mobile base reaches the vicinity of the target, the manipulator planning and control module becomes active. It starts with task allocation and trajectory generation, commonly achieved using sampling-based planners like RRT. This is followed by motion planning and control, which handles inverse kinematics (IK), torque control and visual servoing to execute precise arm movements toward the target. Finally, the soft gripper control module ensures successful interaction with the object. Grasping and control uses tactile/contact feedback

Table 4 Overview of soft mobile manipulators

Crop	System	End-effector	Perception	Metrics	Motion planning	References
Strawberry	Cartesian arm wheeled base	5-finger (PLA)	YOLOv4	Picking rate: 71.7%	Joint angle control with encoder feedback	Tituaña <i>et al.</i> (2024)
Tomato	Dual arm differential drive	3-finger pneumatic	Mask-RCNN	Picking rate: 73.04%, time: 11 s	Visual end-effector servoing-	Gong <i>et al.</i> (2022)
Strawberry	Husky dual UR3 arm mobile robot	3D printed multi-fingered	GAN	Mean joint angle error: 2.8835 mm	ANN trained via robot babbling for motion mapping	Wang <i>et al.</i> (2023b)
Apple	UR5 arm tracked drive	3-finger-based	Mask-RCNN	Harvesting rate: 81% (crowded), 91% (ideal)	Movelt with TRAC-IK for inverse kinematics	Kang <i>et al.</i> (2020)
Apple	UR5 arm wheeled base	Tapered vacuum hybrid	Mask-RCNN	Detachment rate: 75.86%, Damage rate: 4.55%	RRT-Connect + PRM* for harvesting in dense orchards	Wang <i>et al.</i> (2023a)
Apple	Cartesian arm 4WD base	3-finger pneumatic	DCNN	Harvesting rate: 80.45%	Multi-agent PPO for arm coordination and path planning	Li <i>et al.</i> (2023a)
Plum	UR5 arm mobile base	4-finger pneumatic	YOLOv3, Retinanet	Harvesting rate: 42%	Visual servoing + sensor fusion for cluttered scenes	Brown and Sukkarieh (2021)
Forsythia	UR5 arm differential drive	Wool pen + Robotiq F85	YOLOv5, YOLACT++, DETR	Pollination rate: 86.19%	Circular trajectory visual servoing	Yang <i>et al.</i> (2023)
Tomato	Differential drive	3-fingered (PLA)	HSV model	Picking rate: 92.45%	Visual servoing with HSV color-based tracking	Shi <i>et al.</i> (2020)
Tomato	Aubo i5 6-DOF arm mobile base	Auxiliary fingered vacuum	YOLOv5	Picking rate: 72.1%, time: 14.6 s	Alternating locomotion-picking with dynamic planning	Rong <i>et al.</i> (2022)
Apple and pear	Dual-arm mobile base (UR5 and UR3)	Vacuum actuated	Camera + depth	Harvest cycle: 10.87 s	T-RRT path planning + 3D collision modeling	Yoshida <i>et al.</i> (2022)
Guava	6-DOF arm on mobile base	Suction gripper	Depth camera	Harvest success: 90.9%	DDPG-based deep RL for collision-free arm planning	Lin <i>et al.</i> (2021)
Vineyard spraying	7-DOF Kinova arm Track-drive	Spray nozzle	Multisensor fusion	RMS tracking error: 4.32 mm	MPC-based coordinated base- arm trajectory control	Yuan <i>et al.</i> (2022)

Source(s): Authors' own work

Figure 10 Overview of a typical agricultural mobile manipulator architecture consisting of perception, motion planning and control modules for the mobile base, manipulator and soft gripper



Source: Authors' own work

for closed-loop control, while Gripper Actuation involves mechanisms like pneumatic or vacuum-based systems, as discussed in Section 3, to grasp the fruit delicately without causing damage.

Each subsystem communicates in real-time, enabling adaptive decision-making that is essential for efficiency and success in field tasks gripper grasps the target with the appropriate force for harvesting securely. This entire process requires coordination between perception, base path planning, manipulation, gripper actuation and control, with each stage dynamically adapting to environmental conditions and specific task requirements. The effectiveness of this workflow directly impacts harvesting success rates and cycle time.

8.2.1 Manipulator planning and control

While the base tackles navigation challenges, the manipulator faces its own set of planning hurdles. These arms need to perform precise tasks like pruning and harvesting, often in cluttered and dynamic environments. One of the most used manipulation methods in agricultural mobile manipulators is visual servoing (Jun *et al.*, 2021; Shi *et al.*, 2020). This technique leverages vision data to guide the end effector toward its target. The system calculates end effector velocities needed to reach the target object based on its unit vector direction. Some implementations (Tituaña *et al.*, 2024) directly actuate joint angles and create a closed-loop control system using encoder feedback. Other approaches (Kang *et al.*, 2020) use the MoveIt library in ROS for TRAC-IK-based manipulator motion planning. Study by Yang *et al.* (2023) extends visual servoing techniques to precision pollination, introducing a novel approach that involves aligning the end-effector with flower pistils using a circular search trajectory.

Vision-based control systems integrated with machine learning algorithms represent a significant advancement. Study Visentin *et al.* (2023) achieved exceptional precision with 2.6% measurement error in visual servo control across 0–4 N force range, using marker tracking combined with K-nearest regressor, support vector regression and deep convolutional neural networks. Advanced optimization approaches have shown promising results. Wu *et al.* (2024) describe an ant colony algorithm implementation. For

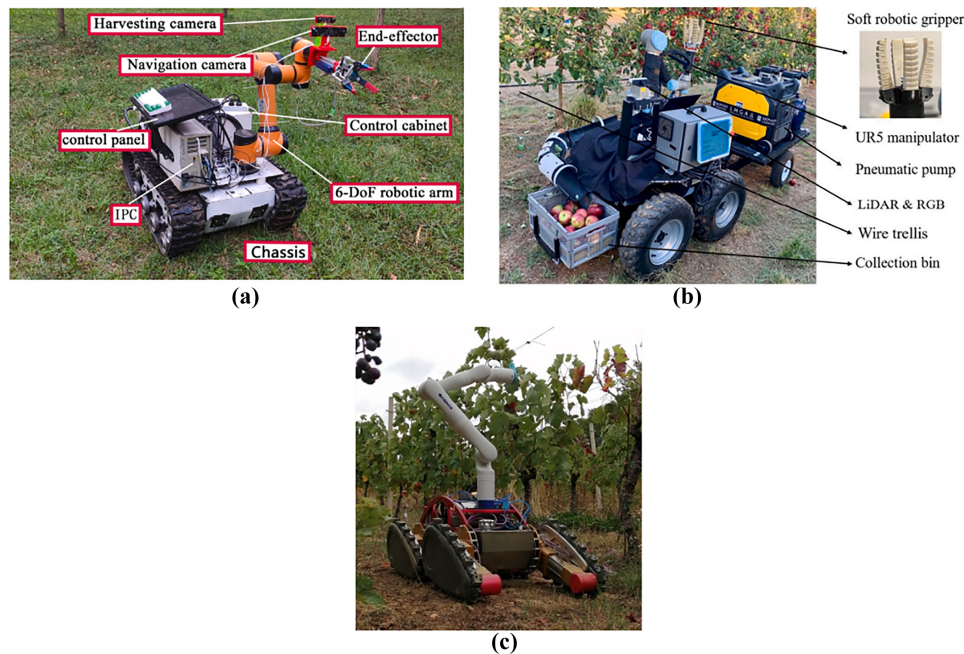
optimizing tea-picking operations, research by Guo *et al.* (2024) presents an enhanced trajectory-planning approach that combines ant colony optimization with genetic algorithms for safflower harvesting, reducing path lengths by 1.33%–7.85% and harvesting time by 28.25%–35.18%. A deep learning approach developed by Wang *et al.* (2023b) uses robot babbling to train an ANN, controller, creating an efficient mapping between joint angles and end-effector positions

8.2.2 Coordinated planning and execution

Coordinated path planning for mobile manipulators presents unique challenges and opportunities. Chen *et al.* (2024b), as shown in Figure 11(a), present a comprehensive approach to autonomous fruit harvesting in orchards, integrating path planning for both mobile platforms and robotic arms. The system uses a yield-driven destination estimation method and an improved multi-map fusion strategy for efficient locomotion control, with YoloV4 object detection to identify fruit clusters and determine optimal destinations. For navigation, the robot uses visual odometry, incorporating camera-lidar mapping to create accurate 3D maps of the orchard environment. The robotic arm's path planning leverages dynamic visual sampling modes (multi-distance and multi-view) for precise fruit positioning, with picking poses estimated based on fruit-stem relationships. Coordination between locomotion and picking is achieved through real-time visual information processing. The system alternates between locomotion and picking states, managed via external IO ports, ensuring efficient operation cycles. Performance metrics showed promising results, with the destination estimation algorithm achieving an average recall of 87.5% in identifying fruit-clustered regions. Another significant implementation by Wang *et al.* (2023a), shown in Figure 11(c), uses a mobile manipulator designed for dense orchard environments, using sensor fusion with LiDAR and RGBD camera technologies for navigation and manipulation planning. Using the ROS MoveIt stack integrating RRT connect and probabilistic roadmap (PRM*) algorithm, the manipulator executes a precise harvesting sequence.

Research by Yoshida *et al.* (2022) implemented a dual-arm mobile manipulator for pear and apple harvesting, combining UR5 and UR3 robotic arms. This system introduced the transition-

Figure 11 Agricultural mobile manipulators (a) 6-DoF tracked drive, (b) 7-DoF vineyard spraying and (c) vacuum hybrid orchard based



Source: (a) [Chen et al. \(2024b\)](#), (b) [Yuan et al. \(2022\)](#), (c) [Wang et al. \(2023a\)](#)

based rapidly exploring random tree (T-RRT) algorithm for path-planning. The approach creates a 3D model of robot joint angles and fruit positions for precise collision detection and path optimization. The system can dynamically navigate between fruits, prioritize arm movements and decide when to abandon difficult picking scenarios. The system demonstrated a complete harvesting cycle of 10.87 s, with planning averaging 2.61 s.

Deep reinforcement learning has emerged as a particularly promising approach for agricultural mobile manipulators. Study [Li et al. \(2023a\)](#) introduced a multi-arm mobile manipulator planning framework using multi-agent reinforcement learning with the proximal policy optimization (PPO) algorithm. This approach treats harvesting as a vehicle routing problem to minimize idle time and traversal distances. The system defines specific actions and states for each robotic arm and incorporates a reward mechanism that encourages efficient harvesting strategies, reducing average cycle time by 33.3% and achieving picking success rates between 71.28% and 80.45%. On the same lines, [Lin et al. \(2021\)](#) used a deep reinforcement learning for guava harvesting using a 6-DOF robotic arm with a recurrent deep deterministic policy gradient (DDPG) algorithm for collision-free path planning. The system learns from past experiences through simulation training, using a reward system that awards 10 points for successful fruit picks and penalizes collisions with −10 points. This method achieved a 90.90% success rate in simulations and showed substantial improvements in field tests compared to traditional methods like Bidirectional RRT, with grasp success rates improving by 19.43%, detachment success rates by 9.11% and overall harvest success rates by 10.97%. Beyond harvesting, mobile manipulators are expanding to precision agricultural tasks like targeted crop treatment. An implementation for vineyard spraying ([Yuan et al., 2022](#)), shown

in [Figure 11\(b\)](#), uses a track-drive mobile base with a 7-DoF Kinova Gen3 robotic arm. The integration of MPC enables simultaneous control of the mobile base and the robotic arm's trajectories through structured vine rows. The system operates using three coordinate frames (global, mobile base and spray frame) to generate optimal lawnmower-style trajectories following the canopy boundaries. The control approach constrains the mobile base to linear motion along vine rows while managing the arm in a four-dimensional control space with a constant y -position maintained through a proportional controller. Multiple joint velocity solutions are resolved through quadratic programming, balancing task space velocities with optimal arm positioning. The system implements proportional controllers and multi-objective optimization to ensure precise spray coverage while minimizing joint velocity variations. This allows for trajectory recalculation based on real-time feedback, resulting in impressive precision with a tracking error (RMS) of just 4.32 mm and a maximum error of 22.16 mm.

8.3 Environmental complexity and challenges

Agricultural environments present significant challenges SAMMs, including irregular terrain, variable lighting, dense foliage occlusions, dynamic obstacles and unreliable GPS coverage, which substantially impact system performance.

Agricultural fields often feature rough, uneven surfaces, resulting in 12%–18% wheel slip ([Yépez-Ponce et al., 2023](#)) and limiting maneuverability in tight spaces ([Chen et al., 2024c](#)). Various adaptive solutions have been developed to address these challenges. For greenhouse environments, four-wheel systems with spring-damper suspension ensure continuous ground contact using large rubber wheels and a low center of gravity for stability ([Wang et al., 2024d](#)). For

challenging forested terrains, Yao *et al.* (2025) developed robots with omnidirectional Archimedean screw drives, enabling skid-free movement across loose and semi-fluid media with superior energy efficiency. Tracked crawler systems distribute weight evenly to reduce sinkage on soft soil, incorporating adjustable suspension and height-adjustable sensing gantries (Fu *et al.*, 2024). Field validation in clayey maize fields demonstrated reliable operation under challenging conditions.

In forested areas, greenhouses and under dense crop canopies, GNSS and RTK-GPS signals often degrade due to signal attenuation and multipath errors, compromising autonomous navigation and mapping accuracy. To address these limitations, various sensor fusion and fallback strategies have been developed. For dense forest environments, Yao *et al.* (2025) demonstrated that high-resolution 3D LiDAR fused with IMU data within SLAM frameworks such as LOAM enables continuous localization, while loop closure mechanisms help correct drift during revisits. In open agricultural fields where tall crops and tree canopies affect RTK-GPS reliability, Sun *et al.* (2024) proposed field-VIO, a stereo VIO system combining stereo cameras with IMU for accurate, GNSS-independent localization. This system uses quantitative windows for robust feature tracking under occlusions and repetitive textures, demonstrating superior performance over GPS-only and monocular VIO systems in real-world field trials. For greenhouse environments where GNSS signals are unreliable or unavailable due to metal structures and dense canopies, Yan *et al.* (2022) implemented a visual-IMU-wheel odometry (VIWO) system. By fusing visual data with inertial measurements and wheel encoder feedback, the system compensates for sensor-specific weaknesses, handling IMU drift and visual tracking loss under dynamic lighting or partial occlusion. The VIWO approach enhances pose accuracy and robustness in narrow aisles and dynamic scenes, ensuring continuous, drift-minimized localization through real-time sensor fusion and keyframe-based optimization.

Agricultural environments create perception challenges, including foliage occlusions, fluctuating lighting and poor color contrast (Liu and Liu, 2023). Deep learning systems using YOLO and faster R-CNN enable robust detection even under partial occlusion through multi-feature fusion and improved CNN architectures. Iqbal *et al.* (2020) addressed dense canopy occlusions using hybrid sensing with actuated 2D LiDAR and RGB-D cameras, achieving plant volume estimation error of 1.76% and height error of 3.2% with R^2 values near 0.99. Sensor fusion approaches combining RGB cameras, LiDAR and GNSS create robust semantic maps for reliable perception under visual obstruction (Mwitta and Rains, 2024). For specific applications, Wu *et al.* (2024) developed vision-based systems for tea leaf harvesting using morphological image processing and improved ant colony optimization algorithms to handle dense overlapping leaves and optimize manipulator sequences.

Traditional exhaustive coverage in structured environments like kiwifruit orchards proves inefficient due to uneven fruit distribution. Deep reinforcement learning approaches using improved re-DQN algorithms process real-time LiDAR and RGB-D data to construct fruit location maps and adapt

navigation dynamically (Wang *et al.*, 2023c). These systems prioritize fruit-rich zones, avoid empty areas and generate collision-free, energy-efficient paths. State-of-the-art SAMMs integrate multi-modal sensor fusion for improved localization, adaptive control algorithms for responsive navigation and continuous learning techniques for enhanced generalizability across different crops and field conditions. These comprehensive approaches ensure reliable operation in diverse agricultural environments through robust perception, adaptive mobility, intelligent planning algorithms and GNSS-independent localization strategies.

9. Conclusion and future outlook

SAMMs are revolutionizing agriculture by integrating advanced soft grippers, mobile platforms and intelligent manipulation strategies to enhance labor efficiency, precision and sustainability. This comprehensive review has examined significant advancements across multiple domains, revealing both promising developments and persistent challenges that define the current state and future trajectory of agricultural robotics. A detailed overview of these component-wise implementations across various crops, including tomatoes, apples, guavas and more is presented in Table 5, which summarizes the diverse configurations of SAMMs.

The evolution of soft gripper technologies demonstrates remarkable progress across multiple actuation mechanisms. While pneumatic-actuated systems offer advantages in cleanliness, safety and maintenance, they face challenges in position and speed control due to air compressibility. Jamming-based systems provide unique advantages through transitions between flexible and stiffened states via geometric interlocking and frictional contacts. FRSA offer programmable fiber patterns for adaptable shape matching and higher force output proportional to input pressure, though limited contact areas and force control challenges have been addressed through inextensible layer reinforcement (Zhu *et al.*, 2023) and rigid component integration. Vacuum grippers use airflow generation for grasping non-rigid materials, offering hygiene benefits, low cost and control ease, with recent innovations including VBA (Katugampala *et al.*, 2019), enabling multi-plane motions and origami-inspired surfaces. While magnetic grippers provide compliance and secure gripping advantages, challenges include MR fluid viscosity dependence and implementation costs. Tendon-driven mechanisms, operated through embedded tendons and electric motor systems, provide precise force control for diverse crops from blackberries (Gunderman *et al.*, 2022) to heavier produce like pumpkins and broccoli (Lee *et al.*, 2019).

Hybrid actuation methods represent particularly promising developments, combining multiple techniques for enhanced versatility. Wang *et al.* (2023a) integrated pneumatic actuation with vacuum manipulation using four tapered soft fingers and suction cups, achieving 12 N suction force and 67.65 N pull-out force at 140 KPa. Comparable designs, Gao *et al.* (2024) featured compact structures (314 × 80 × 120 mm) combining vacuum suction and pneumatic detachment for tomato harvesting, though limitations in vacuum effectiveness on tomato calyx have been noted (Rong *et al.*, 2022). Grasping methodology research has revealed critical insights comparing

Table 5 Crop mapping summary table

Crop	Soft gripper type	Actuation	Perception method	Localization methods	Path planning	Reference(s)
Tomato	3-Finger Pneumatic, Hybrid Suction	Pneumatic/vacuum	Mask-RCNN, YOLOv5, HSV	Visual SLAM (ORB-SLAM3), Scan Context + ICP	Visual servoing, deep reinforcement learning (RL)	Gong et al. (2022) , Rong et al. (2022) , Shi et al. (2020)
Strawberry	Fiber-reinforced diaphragm	Pneumatic	YOLOv4, GAN	CBQ-RRT + GPS/IMU	Sampling-based planning	Tituaña et al. (2024) , Wang et al. (2023a)
Apple	3-Finger, Tendon-Driven	Pneumatic/electric	Mask-RCNN, DCNN	AF-PCP, hector SLAM	TRAC-IK, PPO-based multi-agent	Kang et al. (2020) , Li et al. (2023a)
Plum	4-Finger Pneumatic	Pneumatic	YOLOv3, Retinanet	Extended Kalman filter-based odometry	Sensor fusion visual servoing	Brown and Sukkarieh (2021)
Guava	Suction gripper	Vacuum	Depth camera	Hector SLAM	Deep RL-based collision-free planning	Lin et al. (2021)
Cucumber	Silicon suction	Vacuum	Global and local cameras (details not mentioned)	Marker-based or RGB-D SLAM	Coverage path planning	Jo et al. (2024)
Cherry tomato	Telescopic soft gripper	Pneumatic cylinders	RGB-depth camera-based localization	EKF-based SLAM	Sampling/hybrid coverage	Gao et al. (2022)
Apple & pear	Vacuum actuated	Vacuum	RGB depth camera-based localization	3D SLAM / AF-PCP	T-RRT + 3D Collision Modeling	Yoshida et al. (2022)
Blackberries	Tendon-driven	Tendon	Camera-based detection (details not mentioned)	–	–	Gunderman et al. (2022)
Kiwi	Suction + cutting	Vacuum	Depth camera for base navigation	3D SLAM/visual SLAM	Coverage path planning	Fu et al. (2024)
Vineyard spraying	Spray nozzle	–	Multisensor fusion	AF-PCP, LiDAR-GPS	MPC-based coordinated planning	Yuan et al. (2022)
Forsythia (pollination)	Wool pen + gripper	Pneumatic	YOLOv5, DETR	Visual SLAM	Circular trajectory planning	Yang et al. (2023)

Source(s): Authors' own work

fingertip and envelope techniques, with envelope grasping demonstrating superior force generation, achieving 8.87 N at 60 KPa through increased surface contact area and even force distribution ([Zhuang et al., 2023](#)). Advanced slip detection systems represent critical breakthroughs in delicate produce handling, with [Liu et al. \(2024\)](#) developing comprehensive frameworks using Tekscan FlexiForce A201 pressure sensors, achieving real-time detection with sub-50 ms response times. The three-tier response strategy demonstrated 97.3% success rates in preventing drops compared to 82.1% without detection, while reducing bruising by 78%.

Control system advancement includes CTPE with recurrent neural networks, achieving 0.17 ± 0.14 N average error at 25 Hz ([George Thuruthel et al., 2022](#)), while RNN-based systems predict failure direction with 75% accuracy and 85% grasp success ([Averta et al., 2022](#)). Current innovations include flexible-fingered designs enabling multi-orientation harvesting ([Liu et al., 2020](#)), fluidic elastomer actuators offering strong grip capabilities ([Birrell et al., 2020](#)) and JAIST's ROSE gripper using rotating dual-layer elastomer cups mimicking floral movements for adaptive grip with 60% reduced positional accuracy requirements ([Bui et al., 2024](#)).

Agricultural environments present substantial mobility challenges, including irregular terrains causing 12%–18%

wheel slip ([Yépez-Ponce et al., 2023](#)) and limited maneuverability in confined spaces ([Chen et al., 2024c](#)). Adaptive solutions include spring-damper suspension systems for greenhouse environments ([Wang et al., 2024d](#)), omnidirectional Archimedean screw drives for challenging terrains ([Yao et al., 2025](#)) and tracked crawler systems with adjustable suspension for soft soil navigation ([Fu et al., 2024](#)). GNSS degradation in agricultural environments necessitates robust localization alternatives, with advanced systems demonstrating exceptional accuracy. AF-PCP algorithms achieve 2.6–4.6 cm localization accuracy with 79.9% error reduction ([Tan et al., 2024](#)), marker-based systems reach 8.57 cm MAE in dynamic greenhouse conditions ([Zhang et al., 2023a](#)) and VIO-EKF fusion attains 2.27–14.12 cm RMSE with 75%–95% improvement over standalone systems ([Yan et al., 2022](#)). For GNSS-denied environments, stereo VIO systems ([Sun et al., 2024](#)) provide continuous, drift-minimized localization through multi-modal sensor fusion.

Agricultural perception systems address complex challenges, including foliage occlusions, variable lighting and poor color contrast through deep learning approaches using YOLO and faster R-CNN architectures ([Liu and Liu, 2023](#)). Hybrid sensing combining actuated 2D LiDAR and RGB-D cameras achieves remarkable precision with plant volume estimation

errors of 1.76% and height errors of 3.2% (Iqbal *et al.*, 2020), while multi-modal sensor fusion creates robust semantic maps enabling reliable perception under visual obstruction (Mwitta and Rains, 2024). Modern agricultural navigation increasingly leverages machine learning for intelligent path planning, with deep reinforcement learning systems using improved re-DQN algorithms processing real-time sensor data to construct dynamic fruit location maps, reducing path length by 31.56% and traversal time by 35.72% in kiwifruit harvesting (Wang *et al.*, 2023c). The ARAES framework uses SAC algorithms, enabling map-free navigation through distance, progress and safety-based reward systems (Kang *et al.*, 2024a). CNN-based approaches trained on over 12,000 images achieve 89% success rates in challenging lighting conditions, while sensor fusion remains essential despite dense foliage and solar irradiance interference (Guo *et al.*, 2024; Aghi *et al.*, 2020).

Coordinated mobile manipulation systems face significant complexity in agricultural environments. While Hybrid A* and sampling methods reduce planning time (Lu *et al.*, 2024), hierarchical MPC approaches achieve ± 2.1 cm accuracy requirements. Systems like Agri. Q uses manipulability indices (Colucci *et al.*, 2022) but requires enhanced adaptability to dynamic changes. Base-manipulator coordination remains complex in dense crops, with MPC-based solutions achieving 4.32 mm RMS tracking errors in vineyards (Yuan *et al.*, 2022), while multi-arm systems ensure collision avoidance (Li *et al.*, 2023a; Yoshida *et al.*, 2022). Conventional CCPP methods waste up to 22% time in headland turns, whereas hybrid planners (Wang *et al.*, 2024a) and adaptive strategies improve efficiency (Höffmann *et al.*, 2024).

Multi-objective planning successfully balances smoothness, energy efficiency, temporal constraints and obstacle avoidance, with R-SAC enabling 83% collision-free paths (Yang *et al.*, 2022) and specialized systems achieving 98.7% task completion rates in grape-sampling applications (Colucci *et al.*, 2023). SAMM's approach to field viability through deep reinforcement learning enables real-time navigation without pre-mapped environments and neural-network controllers mastering complex manipulation tasks (Wang *et al.*, 2023b). Hybrid actuators provide precise grasping forces ranging from 0.1 to 15 N while maintaining <5% crop damage rates (Wang *et al.*, 2024e). The soft gripper market demonstrates strong growth potential with a projected 24.6% expansion by 2028 (Liu *et al.*, 2023). Collaborative frameworks using reinforcement and federated learning enable coordinated multi-SAMM operations (Li *et al.*, 2023a; Ferdaus *et al.*, 2024), reducing operational costs by \$18–\$24 per acre for weeding and \$12–\$15 for monitoring activities. Multi-agent systems demonstrate operational efficiency improvements with up to 35.18% faster harvesting rates (Guo *et al.*, 2024) and 94.1% picking success rates using advanced soft grippers (Fu *et al.*, 2024).

Critical research priorities must address unified control framework development, integrating navigation and manipulation, robust perception system advancement for diverse environmental conditions and energy-efficient design optimization. Deployment readiness requires achieving sub-5 cm positioning accuracy, maintaining total system costs below \$15,000 and ensuring reliable 8-h operational capabilities. Future research should particularly focus on overcoming

persistent gripper adaptation challenges for varying produce sizes, enhancing operational efficiency to compete with traditional harvesting equipment and reducing infrastructure requirements for pneumatic and electric systems. Continued integration of vision-based control systems with machine learning algorithms presents significant opportunities for addressing current limitations. The convergence of advanced perception, intelligent planning and adaptive manipulation technologies positions SAMMs for transformative impact in sustainable agricultural automation.

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Further reading

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