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Review

A review on multirobot systems in agriculture

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ABSTRACT

Agricultural multirobot systems (MRSs) are expected to be essential in future agriculture. Therefore, MRSs comprising an aerial robot, a ground robot, and a manipulator are being actively studied for application in agriculture. However, MRSs are still being researched and several challenges need to be addressed. Moreover, no comprehensive surveys or detailed analyses of agricultural MRSs exist. Therefore, we systematically investigated and reviewed an MRS used in agriculture in terms of platforms, control, and application. This review primarily considers state-of-the-art research on agricultural MRSs and covers the developed platforms and controls applied to the field with subtasks. Furthermore, we introduce recent trends and analyze the problems and limitations of various MRSs. Finally, we discuss the points that need to be considered for commercializing agricultural MRSs and the expansion of their applications to the fields of geosciences and life sciences. Future research on the proposed agricultural MRS can help with advancements in the robotics market.

1. Introduction

Smart farming and digital agriculture have become crucial to address food shortages caused by complex factors such as decrease in the agricultural population, dwindling workforce owing to an aging population, and increase in cultivation uncertainty owing to climate change. Precision agriculture is a classic approach that maximizes crop production while minimizing input resources such as fertilizers, labor, water, and pesticides by utilizing various information and communication technologies (ICT) (Zhang et al., 2002; Sott et al., 2020). Thus, it has gained considerable attention as a novel agriculture technique because it collects information on factors affecting plant cultivation and enables an optimized farming efficiency through precision analysis (McBratney et al., 2005). Recently, smart farming, a concept of advanced precision agriculture, has emerged as a new paradigm of the fourth Industrial Revolution, along with agriculture (Abbasi et al., 2022; King et al., 2017; O'Grady and O'Hare, 2017; da Silveira et al., 2021). Smart farms utilize technologies such as the Internet of Things (ICT, artificial intelligence (AI), big data, cloud computing (Sharma et al., 2020; Ren et al., 2020; Friha et al., 2021), and robots in the production, processing, and distribution stages to optimize production efficiency and work convenience (R Shamshiri et al., 2018). Moreover, robots have the potential to achieve automation and unmanned, intelligent, and advanced agriculture (Wang et al., 2021a). Alongside smart farming, a new paradigm called "digital agriculture" has been developed. Digital agriculture entails studying agricultural areas using big data as well as robots and AI to realize convenience and productivity through crop management, intelligent cultivation, and innovative distribution. Aerial robots (Zhang and Kovacs, 2012), ground robots, and robotic arms (i.e., manipulators) have been actively introduced for automation and unmanned farming (Fountas et al., 2020; Duckett et al., 2018). These agricultural robots have remarkable maneuverability and scalability; thus, they offer substantial advantages in terms of data collection and crop management through remote sensing (Liaghat et al., 2010; Thorp and Tian, 2004; Ge et al., 2011).

The use of agricultural robots, which can address labor shortages and optimize long-term cost (Pedersen et al., 2006; Marinoudi et al., 2019; Vougioukas, 2019), is growing at a considerably faster rate, despite slower industrial development, than other industrial ecosystems. In particular, unmanned aerial vehicles (UAVs) can rapidly survey and spray over large areas; therefore, they are generally applied in various fields for tasks such as monitoring, crop counting, yield prediction, pest detection (Temniranrat et al., 2021), and spraying (Kim et al., 2019b). In addition, unmanned ground vehicles (UGVs) capable of replacing traditional tractors, combine harvesters, and transplanters were introduced, and a multipurpose UGV system was developed for harvesting (Bac et al., 2014), transplanting, seeding, mapping, and

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irrigation of various crops such as apples, tomatoes, strawberries, and melons) (Bechar and Vigneault, 2016). Therefore, the applications of agricultural robots have expanded outdoors and to horticulture facilities. Furthermore, robotic technologies, including localization, control, path/motion planning, navigation, and performance evaluation using working tools such as LiDAR, cameras, end-effectors, gas sensors, and radio telemetry, have achieved considerable progress (Bechar and Vigneault, 2017; Oliveira et al., 2021a). However, because of the characteristics of agricultural environments (i.e., crop diversity, robot platforms, agricultural tasks, and areas), evolution toward future agriculture is slow. Nevertheless, an agricultural multirobot system (MRS) has recently been studied as a solution (Roldán et al., 2018) to improve task efficiency.

MRS-based cooperation exhibits an advantage in terms of system reliability owing to certain characteristics, such as flexibility, which allows it to cope with a task, even if a specific robot fails, and exhibit higher operation efficiency than a single robot system. MRSs are based on the cooperation among multiple agents and division of labor. However, several technical challenges exist when commercializing MRSs. This is because individual robots, multiple robots, and integrated system technologies are being simultaneously developed (Parker, 2000). For example, when many people perform cleaning tasks, their collaboration can be classified as strong cooperation, wherein they carry heavy objects through direct interaction, and weak cooperation, wherein each individual is assigned missions and regions to perform localized tasks. For strong cooperation in MRS systems, problems, such as coordination between robots, for example, formation/swarm control (Yan et al., 2013), and controlling the force and driving velocity of the robot, for example, adaptive force/velocity control, exist. Weak cooperation has notable advantages such as the ease of identifying how to optimize the working area considering collision avoidance between robots, assigning various priority-based tasks to each robot (e.g., dynamic/weighted task allocation) (Khamis et al., 2015), and performing system management under different failure scenarios (fault detection and diagnosis) (Khalastchi and Kalech, 2019). Recently, the cooperation between heterogeneous robot-based MRSs to achieve full automation has been actively researched (Rizk et al., 2019). The ability of a heterogeneous MRS to perform various tasks in any environment further increases its practicality and usability. Nevertheless, the commercialization of MRS-based applications, which are not limited to factories, research fields, and specific services and can be applied in various industries, remains an inevitable challenge.

Therefore, element technologies are being actively researched towards introducing MRSs into agriculture (Chevalier et al., 2015; Thomasson et al., 2018; Vu et al., 2018; Carbone et al., 2018). However, these previous studies were conducted at an early stage of the practical application of agricultural robots. In particular, in an unstructured context, such as agriculture, robots are subjected to various environmental factors. Therefore, the diversity of robot systems must be considered. For example, depending on the climate, different decisions must be made by an agricultural robot system, and when multiple robots are applied, the reliability of the system must be ensured to realize the prioritization and distribution of work and diagnosis in the case of robot failure. As mentioned above, owing to the diversity and complexity of the agricultural environment, the technological capabilities required to implement MRS in a real environment are yet to be achieved. To address the labor shortage problem by building an infrastructure involving multiple robots to improve production efficiency, existing problems should be reviewed and discussed through systematic surveys of the current agricultural MRSs (Dutta et al., 2021; Mao et al., 2021; Ribeiro and Conesa-Muñoz, 2021; Albiero et al., 2022; Lytridis et al., 2021). A few studies focused on applications or included rough reviews; however, we thoroughly investigated modeling, control, and applications and discussed further applications, current steps, commercialization, challenges, and directions for future development. Therefore, in this paper, we strictly present a detailed review of state-of-the-art literature on platforms, control, and applications of MRSs for agriculture, and we discuss future challenges.

In particular, we investigated the robot platform types, primary controls, and primary applications in agriculture. Furthermore, we discuss potential challenges and issues in terms of commercialization, cooperative manipulation, and further applications in geoscience and life science. In this study, the current status, problems, and development directions of the state-of-the-art articles for agricultural MRSs were systematically compared and analyzed. Therefore, this review was aimed at assisting researchers working on agricultural robot to identify useful platforms and controls for their applications and discuss the technologies that have already been studied for the development of the desired robot system. The objective is to provide a comprehensive review of MRSs to draw a guide map by presenting approaches that, in our opinion, are promising and prominent.

The remainder of this paper is organized as follows. MRS modeling and its platforms, including ground vehicle types, aerial vehicle types, mobile manipulator types, multiple UGV, multiple UAV, multiple manipulators, and heterogeneous robots are described in Section 2. In Section 3, motion control and obstacle avoidance, which are high-level controls from a single-robot perspective, as well as localization and mapping are examined. Furthermore, passive collaboration, active collaboration, and cooperative manipulation control in terms of collaboration in MRSs are discussed. Section 4 presents a review of the tasks for which MRSs are applied. In Section 5, the commercialization of MRSs, cooperative manipulation, and potential applications of MRSs in fields of life science and geoscience are examined. Finally, the conclusions are presented in Section 6.

2. Platforms

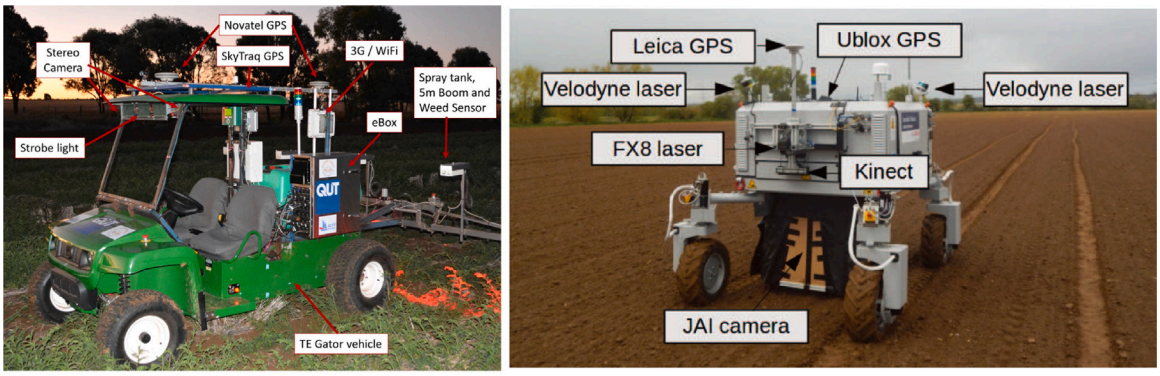
In this section, we review various robots, such as UGVs, UAVs, and manipulators, used in agricultural tasks. Furthermore, we review MRS and heterogeneous MRSs, which comprise different types of platforms (Roldán et al., 2018).

2.1. Ground vehicle type

As shown in Fig. 1(a), several agricultural vehicles such as tractors, sprayers, rotary tillers, planters, and combine harvesters have been developed. Workers ride on these machines or drive them. However, the development of unmanned agricultural vehicles have been actively researched (Fig. 1(b)). These vehicles operate by sensing and do not require any user input (Cheein and Carelli, 2013; Ball et al., 2017; Roshanianfard et al., 2020). The mechanical platform requires awareness of the surrounding environment and working decisions to perform automated farming. UGVs for agriculture can be divided into two types: automated conventional agricultural vehicles and mobile platforms developed specifically for agricultural tasks (Gonzalez-De-Santos et al., 2020; Xu and Li, 2022).

Using conventional agricultural vehicles to configure a mobile platform ensures more robust, reliable, and efficient modification/extension of the system (Gonzalez-de Santos et al., 2017). In the agricultural field, tractors are the primary vehicles used for planting, spraying, fertilizing, harvesting, hauling, and mowing purposes. Automation and robotics are required to increase tractor productivity. Tractors are automated by equipping them with various sensors and control algorithms to perform tasks. They can be equipped with a GPS system, control, sensing (vision), and actuating systems (Gonzalez-de-Soto et al., 2016; Ball et al., 2016).

The second type of UGV development for agricultural tasks is a specifically designed mobile platform (Mueller-Sim et al., 2017; Bak and Jakobsen, 2004; Chebrolu et al., 2017). Mobile platforms can be classified according to their number of wheels. Most field robots



(a) (b)

Fig. 1. Different types of UGVs: (a) conventional agricultural vehicle (Ball et al., 2016); (b) agricultural robot with four-wheel steering (Chebrolu et al., 2017).

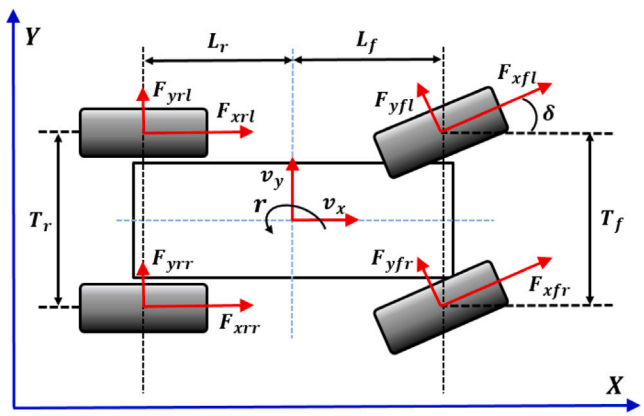


Fig. 2. Schematic of the kinematics model for a 3DOF four-wheel robot.

are four-wheeled and are thus capable of maximum static and dynamic stability (Garcia and de Santos, 2006). However, a platform that consists of three wheels exists, which is the minimum number required to ensure static stability (Ball et al., 2017). Mobile platforms that are manufactured for farming can easily perform certain tasks. Furthermore, their lightweight design makes them less expensive and makes for minimal soil compression. However, they have limitations, such as the inability to perform tasks on inclined surfaces, lack of dynamic safety systems, and inability to reschedule or solve problems by themselves.

A kinematic model of a 3DOF four-wheeled robot that serves as a representative of UGVs is illustrated in Fig. 2. The local coordinate frame attached to the center of the body is denoted by $L(x, y)$, where x and y are the lateral and longitudinal coordinates, respectively. The dynamic equations of a four-wheeled robot are described in Chu et al. (2010): $\dot{v}_x = v_y r + \frac{1}{m}[C_\delta \cdot (F_{xfl} + F_{xfr}) - S_\delta \cdot (F_{yfl} + F_{yfr}) + F_{xrl} + F_{xrr}]$, $\dot{v}_y = -v_x r + \frac{1}{m}[S_\delta \cdot (F_{xfl} + F_{xfr}) - C_\delta \cdot (F_{yfl} + F_{yfr}) + F_{yrl} + F_{yrr}]$, $\dot{r} = \frac{1}{I_z}[L_f(F_{xfl} + F_{xfr}) \cdot S_\delta + L_f(F_{yfl} + F_{yfr}) \cdot C_\delta - L_f(F_{yrl} + F_{yrr}) - \frac{T_f}{2}(F_{yfl} + F_{yfr}) \cdot C_\delta + \frac{T_f}{2}(F_{yfl} + F_{yfr}) \cdot S_\delta + \frac{T_r}{2}(F_{xrl} + F_{xrr})]$, where δ is the steering angle of the front wheels, $S_\delta = \sin(\delta)$, and $C_\delta = \cos(\delta)$. v_x, v_y, and r are the vehicle longitudinal velocity, lateral velocity, and yaw rate, respectively; F_{xfl}, F_{xfr}, F_{xrl}, and F_{xrr} indicate the vehicle front left, front right, rear left, and rear right longitudinal tire forces, respectively; F_{yfl}, F_{yfr}, F_{yrl}, and F_{yrr} are the vehicle front left, front right, rear left, and rear right lateral tire forces, respectively; L_f and L_r indicate the front and rear wheel base lengths, respectively. T_f and T_r are the front and rear track widths, respectively; and I_z and m are the moments of vehicle inertia, in terms of the yaw axis and vehicle mass, respectively.

2.2. Aerial vehicle type

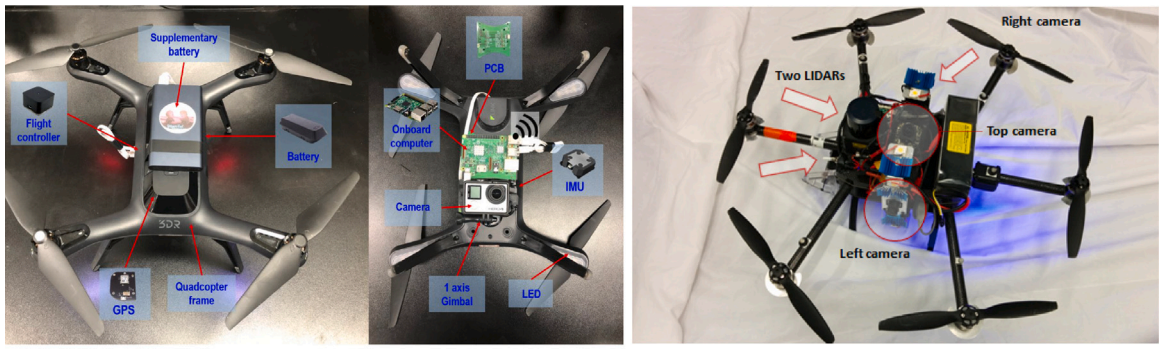
The utilization of UAVs in agricultural fields as a replacement for aircraft and satellites is rapidly increasing (del Cerro et al., 2021). UAVs can fly at lower altitudes, enabling them to easily obtain high-quality images (Feng et al., 2021). In addition, compared with UGVs, UAVs can perform various farming tasks, regardless of soil type and surface inclination. Depending on the tasks and properties of the farming area, various technologies are required to apply UAVs to agriculture. The wings of UAV can either be fixed or rotary. A fixed-wing UAV resembles an airplane and lifts itself by creating an aerodynamic thrust. Consequently, it is generally larger than a rotary-wing UAV and can fly for longer periods of time. Therefore, it has been employed to monitor, sense, and spray vast areas (Zarco-Tejada et al., 2013; Pederi and Cheporniuk, 2015). Two types of rotary-wing UAVs exist, helicopters and multirotors. There is a giant propeller on top of the platform of a helicopter-type UAV, which is often used for aerial imaging and spraying, similar to fixed-wing UAVs (Lan et al., 2017; Pounds et al., 2012). As shown in Fig. 3, multirotor UAVs are classified based on the number of rotors into quadcopters (four rotors) (Torres-Sánchez et al., 2015), hexacopters (six rotors) (Özaslan et al., 2016), and octocopters (eight rotors) (Dai et al., 2017). The UAV payload is directly proportional to the number of rotors. However, for these UAVs, because taking off/landing and motion control are complex, their platforms are designed for specific purposes.

Furthermore, we describe the kinematic and dynamic models of the quadcopter, which is the most well-known among UAVs. The quadcopter contains four motors with four corresponding input forces, which are the thrust forces provided by each propeller (Fig. 4). Using the vector $\boldsymbol{\xi}$, the quadcopter's linear position is determined in the inertial frame with x, y, z axes. In the inertial frame, the attitude $\boldsymbol{\eta}$ (i.e., angular position) includes three Euler angles, namely the pitch θ, roll ϕ, and yaw angles ψ. The linear and angular position vectors are contained in vector $\boldsymbol{q}$: $\boldsymbol{\xi} = [x\ y\ z]^T, \boldsymbol{\eta} = [\phi\ \theta\ \psi]^T, \boldsymbol{q} = [\xi\ \eta]^T$.

The origin of the body frame of the quadcopter is located at its center of mass. In this body frame, the linear velocities are denoted as $\boldsymbol{V}_B$ and the angular velocities are denoted as $\boldsymbol{\nu}$ with body rotation rates p, q, and r defined as $\boldsymbol{V}_B = [v_x\ v_y\ v_z]^T, \boldsymbol{\nu} = [p\ q\ r]^T$. The rotation matrix from the body frame to the inertial frame is given by the following:

$$\boldsymbol{R} = \begin{bmatrix} C_\psi C_\theta & C_\psi S_\theta S_\phi - S_\psi C_\phi & C_\psi S_\theta C_\phi + S_\psi S_\phi \\ S_\psi C_\theta & S_\psi S_\theta S_\phi + C_\psi C_\phi & S_\psi S_\theta C_\phi - C_\psi S_\phi \\ -S_\theta & C_\theta S_\phi & C_\theta C_\phi \end{bmatrix} \tag{1}$$

The rotation matrix $\boldsymbol{R}$ is orthogonal; therefore, the rotation matrix from the inertial frame to the body frame is $\boldsymbol{R}^{-1} = \boldsymbol{R}^T$. The transformation matrix for angular velocities from the inertial frame to the body frame is defined as $\boldsymbol{W}_\eta$, and the transformation matrix from the body



(a) (b)

Fig. 3. Different types of UAVs: (a) quadcopter (Ju and Son, 2018b); (b) hexacopter (Özaslan et al., 2016).

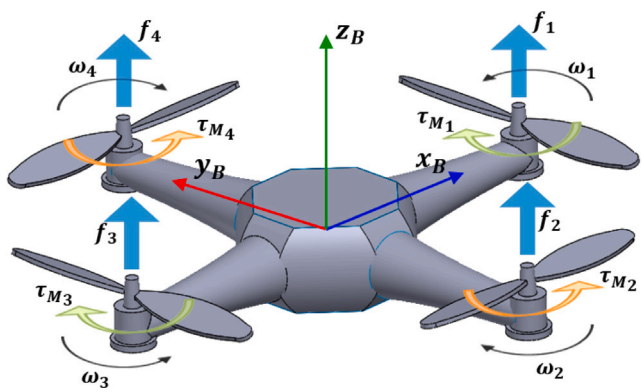


Fig. 4. UAV modeling.

frame to the inertial frame is denoted as $\boldsymbol{W}_\eta^{-1}$ (Alderete, 1995).

$$\dot{\boldsymbol{\eta}} = \boldsymbol{W}_\eta^{-1}\boldsymbol{\nu}, \begin{bmatrix}\dot{\phi}\\ \dot{\theta}\\ \dot{\psi}\end{bmatrix} = \begin{bmatrix}1 & S_\phi T_\theta & C_\phi T_\theta\\ 0 & C_\phi & -S_\phi\\ 0 & S_\phi/C_\theta & C_\phi/C_\theta\end{bmatrix}\begin{bmatrix}p\\ q\\ r\end{bmatrix},$$
$$\boldsymbol{\nu} = \boldsymbol{W}_\eta\,\dot{\boldsymbol{\eta}} \begin{bmatrix}p\\ q\\ r\end{bmatrix} = \begin{bmatrix}1 & 0 & -S_\theta\\ 0 & C_\phi & C_\theta S_\phi\\ 0 & -S_\phi & C_\theta C_\phi\end{bmatrix}\begin{bmatrix}\dot{\phi}\\ \dot{\theta}\\ \dot{\psi}\end{bmatrix}, \tag{2}$$

where $T_x = \tan(x)$. Matrix $\boldsymbol{W}_\eta$ is invertible, if $\theta \neq (2k-1)\phi/2, (k \in \mathbb{Z})$, where $\mathbb{Z}$ denotes the set of all integers. The quadcopter is considered to have a symmetrical structure, with its four arms aligned with the $x-$ and $y-$axes of its body. Therefore, the inertia matrix becomes a diagonal matrix $\boldsymbol{I} = diag(I_{xx}, I_{yy}, I_{zz})$, where $I_{xx} = I_{yy}$.

The angular velocity of rotor i, represented as ω_i, produces a force f_i in the direction of the rotor axis. Moreover, the angular velocity and acceleration of the rotor produce a torque τ_{M_i} around the rotor axis defined as $f_i = k\,\omega_i^2$, $\tau_{M_i} = b\,\omega_i^2 + I_M\,\dot{\omega}_i$, where k, b, and I_M are the lift constant, drag constant, and moment of inertia of the rotor, respectively. $\dot{\omega}_i$ because its effect is negligible. The combined forces of the rotors produce thrust T in the body's z-axis direction. The torques τ_{phi}, τ_{theta}, and τ_{psi} in the direction of the body frame angle makeup torque τ_B are defined as $T = \sum_{i=1}^4 f_i = k\sum_{i=1}^4 \omega_i^2$, $T_B = [0\ 0\ T]^T, \tau_B = [\tau_\phi\ \tau_\theta\ \tau_\psi]^T = [lk(-\omega_2^2 + \omega_4^2)\ lk(-\omega_1^2 + \omega_3^2)\ \sum_{i=1}^4 \tau_{M_i}]^T$, where l is the distance between the center of mass of the frame and the rotor. Consequently, the roll movement is accomplished by lowering the velocity of the second rotor while increasing that of the fourth rotor. Similarly, the pitch movement is caused by the first rotor's velocity being reduced, whereas the third rotor's velocity is reduced. The angular velocity of the two opposing rotors is increased and the angular velocities of the other two rotors are reduced to achieve yaw movement.

2.3. Mobile manipulator type

Mobile manipulators are used for harvesting and cultivation (Bac et al., 2014; Pramod and Jithinmon, 2019; Xiong et al., 2019). Specifically, they are used to harvest relatively light sweet peppers, tomatoes, or heavy watermelons. The manipulator must be combined with a suitable end effector when using it to harvest. Because harvesting methods are determined by the crop, end-effectors must be designed differently depending on the crops being harvested (Seol et al., 2020). Moreover, because the end effector performs a direct operation on the target crop, if its characteristics are unsuitable, it may damage the surrounding stems and fruits during the harvest process. Therefore, an end-effector has the most significant effect on the performance of harvesting robots (Wang et al., 2019). Therefore, it is important to design suitable end effectors to apply robot manipulators to agriculture.

As shown in Fig. 5, an agricultural end-effector comprises grasping and cutting modules, based on the method required for harvesting the target. The crop was fixed with a grasping module to keep it stationary and then harvested by cutting the peduncle of the crop using the cutting module. However, crops can also be harvested by gripping and twisting the crop with a grasping module without using a cutting module (Chiu et al., 2013; Mu et al., 2017) (Fig. 5(a)). The grasping and cutting modules can be jointly attached to a single end-effector (Hemming et al., 2014) (Fig. 5(d)) or each of them can be attached to a different robot arm (Zhao et al., 2016).

The grasping modules employ a method of holding fingers and suction cups. Finger-shaped grasping modules can damage the contact surface of the target crop. To compensate for this shortcoming, considerable research has been conducted on soft grippers (Hohimer et al., 2019; Shintake et al., 2018). Grasping using suction cups can cause less damage to target crops. However, if the precise location of the target crop is not determined, the crop can be damaged when separating it from the peduncle. Furthermore, several grasping modules with characteristics such as parallel (Bachche and Oka, 2013), tendon-driven (Silwal et al., 2017), and bionic fingers (Mu et al., 2017) have been developed (Morar et al., 2020).

The stem of the crop is generally tough owing to its fiber; therefore, various cutting modules other than the usual blade are being developed. A cutting module that separates the peduncle from the fruit using hot arcs created by connecting two electrodes with nichrome wires was proposed (Bachche and Oka, 2013). In Hemming et al. (2014), a cutting module that uses fin-ray fingers to fix the paprika and then harvests it using scissors was proposed. In addition, several cutting modules with components, such as an electric cutter (De-An et al., 2011), vibrating knife (Arad et al., 2020), and oscillating cutting blades (Lehnert et al., 2017) have been proposed.

We considered the inverse kinematic problem of a 6DOF manipulator (Fig. 6). This problem aims to obtain a nonlinear function, f^{-1} for $\boldsymbol{q} = f^{-1}(\boldsymbol{p}, \boldsymbol{R})$, where $\boldsymbol{p}$ and $\boldsymbol{R}$ are the position and orientation of

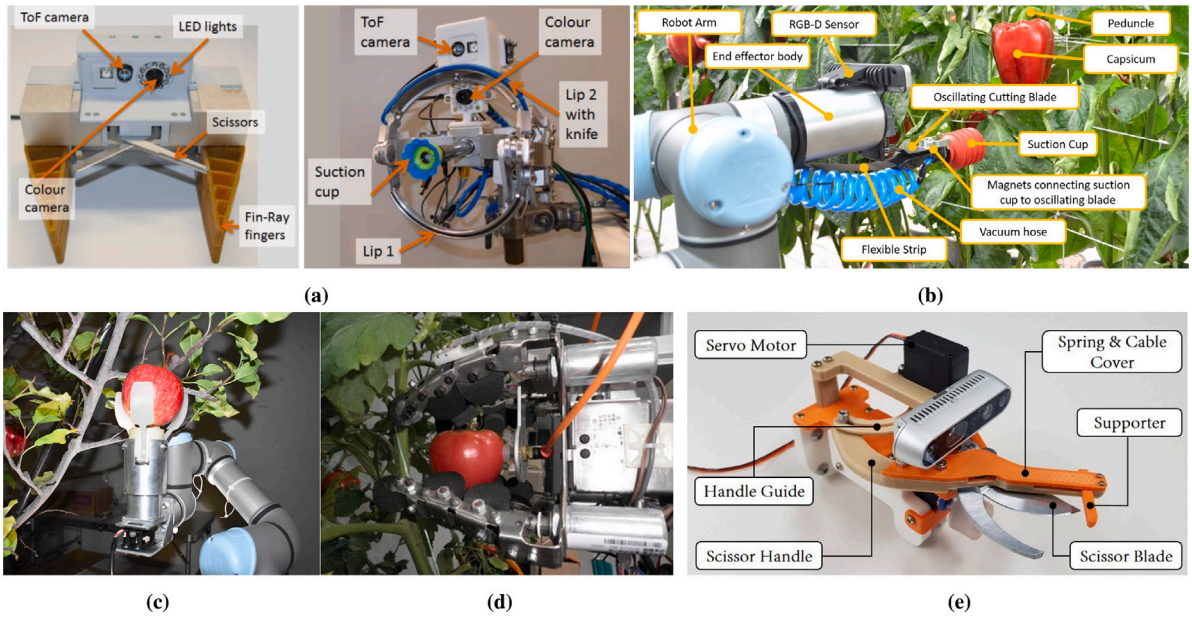


Fig. 5. Different types of end-effectors proposed by: (a) Hemming et al. (2014), (b) Lehnert et al. (2017), (c) Onishi et al. (2019), (d) Chiu et al. (2013), and (e) Jun et al. (2021).

the end-effector, respectively. These are determined by the angle $\boldsymbol{q}$ of each joint in the case of a vertically articulated manipulator. The angle $\boldsymbol{q} = \theta_i$ of each joint can be calculated using inverse kinematics when $\boldsymbol{p} = (p_x, p_y, p_z)$ and $\boldsymbol{R}(\phi, \theta, \psi)$ are given. The rotation matrix $\boldsymbol{R}$ can be expressed using Eq. .

Denavit–Hartenberg notation $\boldsymbol{T}$ is used to calculate the relationship between Links i and $i+1$ (Asada and Slotine, 1986). The homogeneous transformation matrix of the Denavit–Hartenberg and the relationship between the manipulator Denavit–Hartenberg notations are expressed as

$$
{}^{n-1}\boldsymbol{T}_n = \begin{bmatrix} C_{\theta_n} & -S_{\theta_n}C_{\alpha_n} & S_{\theta_n}S_{\alpha_n} & r_nC_{\theta_n}, \\ S_{\theta_n} & C_{\theta_n}C_{\alpha_n} & -C_{\theta_n}S_{\alpha_n} & r_nS_{\theta_n}, \\ 0 & S_{\alpha_n} & C_{\alpha_n} & d_n \\ 0 & 0 & 0 & 1 \end{bmatrix},
$$

$$
{}^{0}\boldsymbol{T}_6 = \begin{bmatrix} & \boldsymbol{R} & \boldsymbol{p} & \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} R_{11} & R_{12} & R_{13} & p_x \\ R_{21} & R_{22} & R_{23} & p_y \\ R_{31} & R_{32} & R_{33} & p_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}
$$

The above equation can be used to calculate the angle $\boldsymbol{q}$ of each joint from $(\boldsymbol{p}, \boldsymbol{R})$ using inverse kinematics. The dynamic equation of the manipulator can be expressed as (Craig, 2009; Spong and Vidyasagar, 2008) $M(\boldsymbol{q})\ddot{\boldsymbol{q}}+C(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}}+\boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{u}$, where $M(\boldsymbol{q})$ is the mass inertia matrix of the system, $C(\boldsymbol{q},\dot{\boldsymbol{q}})$ indicates the centrifugal/Coriolis matrix, $\boldsymbol{g}(\boldsymbol{q})$ is the gravity vector, and $\boldsymbol{u}$ is the input vector. The inverse dynamics can be expressed by $\ddot{\boldsymbol{q}} = M^{-1}(\boldsymbol{q})(\boldsymbol{u} - C(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} - \boldsymbol{g}(\boldsymbol{q}))$, and matrix $M(\boldsymbol{q})$ can be calculated using $M(\boldsymbol{q}) = \left[\sum_{i=1}^{n}\left(m_i J_{v_i}^T J_{v_i} + J_{\omega_i}^T R_i I_i R_i^T J_{\omega_i}\right)\right]$, where J_{v_i} and J_{ω_i} are the linear and angular parts, respectively, of the Jacobian matrix J_i (Craig, 2009; Spong and Vidyasagar, 2008). The passivity property of robotic manipulators, which is the result of the *skew-symmetry* property of the matrix $\dot{M}(\boldsymbol{q}) - 2C(\boldsymbol{q},\dot{\boldsymbol{q}})$ can be used to derive matrix $C(\boldsymbol{q},\dot{\boldsymbol{q}})$. Matrix c_{ij}, which can be obtained from the inertia matrix m_{ij} and gravity vector $g_i(\boldsymbol{q})$ can be expressed as follows: (Craig, 2009; Spong and Vidyasagar, 2008)

$$
c_{ij} = \sum_{k=1}^{n} \frac{1}{2}\left(\frac{\partial m_{ij}}{\partial p_k} + \frac{\partial m_{ik}}{\partial p_j} - \frac{\partial m_{kj}}{\partial p_i}\right)\dot{q}_k, \quad g_i(\boldsymbol{q}) = \frac{\partial P}{\partial q_i} \tag{4}
$$

2.4. MRS

MRSs are gaining significant attention in various agricultural environments owing to their ability to coordinate and reassign missions (Gao et al., 2018a; Minßen et al., 2011). They can be modeled based on graph theory, as shown in Fig. 7. Let us consider that each node is a first-order model of the dynamics of the individual robots defined as $\dot{x}_i = u_i,\ x_i(0) = \xi_i,\ i \in \{1, \dots, N\} =: \mathbb{N},\ u_i = \sum_{j\in\mathbb{N}_i} a_{ij}(x_j - x_i)$, where $x_i \in \mathbb{R}$ is the position status variable, u_i is the usual consensus control for the input of an individual node, ξ_i is the initial value of node i, and $\mathbb{N}$ is the set of nodes connected to node i. Individual nodes i find the difference between their information x_i and the information x_j from the associated node j.

Then, the entire system can be expressed as $\dot{x} = -\boldsymbol{L}x, \quad x(0) = \xi$, where $\boldsymbol{L}$ is the Laplacian of the graph defined by the MRS network that can be calculated using the adjacency matrix and degree matrix. We assumed that $\boldsymbol{V} = \{v_1, \dots, v_n\}$ are a set of vertices in a graph corresponding to the identity of the robots. The adjacency matrix $\boldsymbol{A} = [a_{ij}] \in \{0,1\}^{N\times N}$ is defined as

$$
a_{ij} = \begin{cases} 1 & if \quad \left\|p_i - p_j\right\| \le R \\ 0 & otherwise \end{cases} \tag{5}
$$

where $p_i \in \mathbb{R}^2$ indicates the position, as well as the state, of the robot i.

The degree matrix is a diagonal matrix $\boldsymbol{D} = diag(deg(v_i), \dots, deg(v_M))$, where $deg(v_i)$ is the degree of the vertex v_i, which is the number of vertices adjacent to v_i. In the Laplacian matrix $\boldsymbol{L} = \boldsymbol{D} - \boldsymbol{A}$, the second-smallest eigenvalue is called the algebraic connectivity λ_2, which indicates whether the network is connected. Subsequently, $x(t) = \exp(-\boldsymbol{L}t)\,x(0)$ and Laplacian matrix $\boldsymbol{L}$ are symmetric. Therefore, the eigenvectors v_i for the eigenvalues λ_i of $\boldsymbol{L}$ are all real vectors and are perpendicular to each other. Among these, $\boldsymbol{LV} = \boldsymbol{VA}$ was established because $\lambda_1 = 0$ and $v_1 = 1_N$. Furthermore, because $\exp(-Lt) = V\exp(-At)V^{-1}$, $x(t)$ can be expressed as $x(t) = v_1 e^{-\lambda_1 t}(V^{-1}x(0))_1 + \dots + v_N e^{-\lambda_N t}(V^{-1}x(0))_N$, where $V^{-1}V = I$; therefore, $(V^{-1})_1$, which is the first row of V^{-1}, must be $(1/N)1_N^T$. Then, for all i, we obtain

$$
\lim_{t\to\infty} x_i(t) = \frac{1_N^T x(0)}{N} 1_N,
$$

$$
\lim_{t\to\infty} x_i(t) = \frac{1}{N}\sum_{i=1}^{N} x_i(0) = average\ of\ \left\{x_i(0) : i \in N\right\} \tag{6}
$$

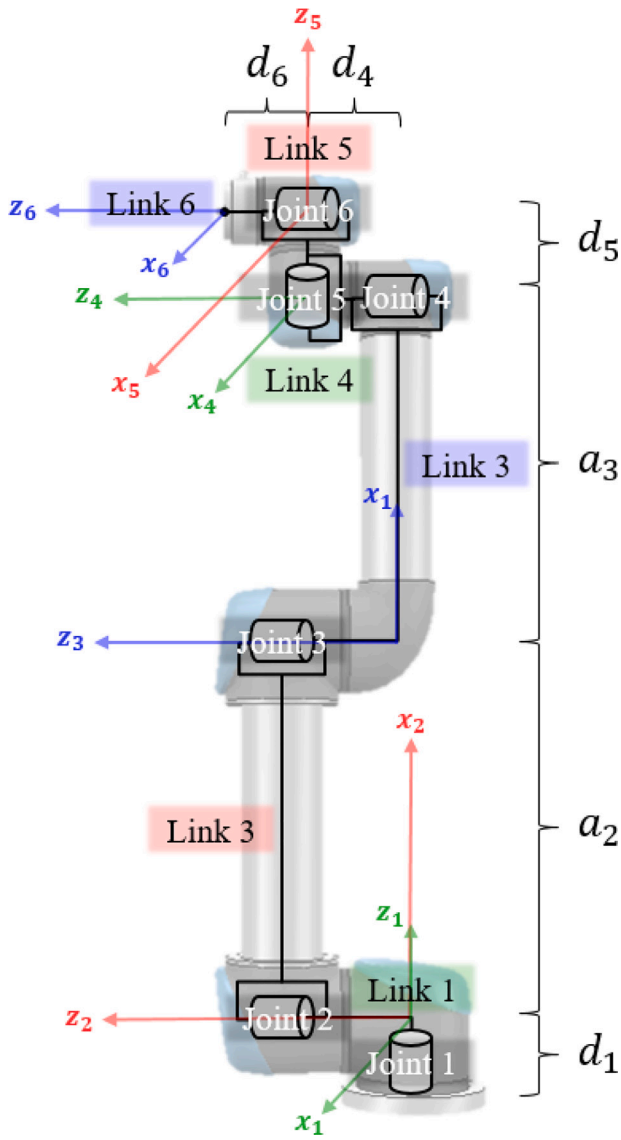


Fig. 6. Manipulator modeling.

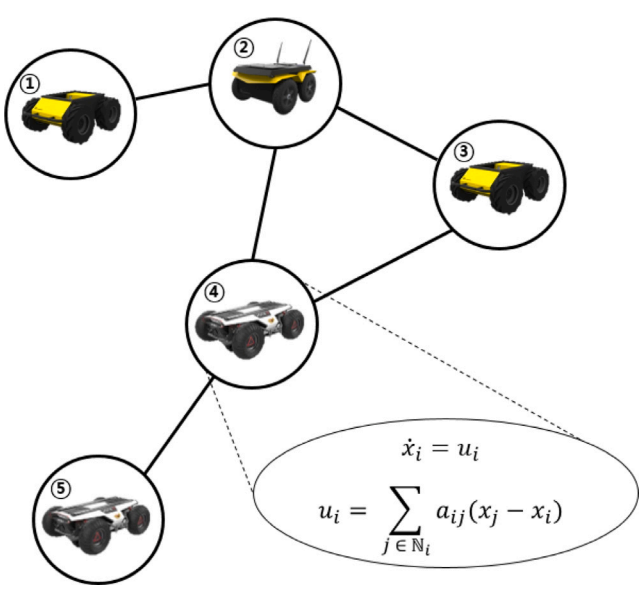


Fig. 7. Graph theory-based modeling for multirobot systems.

Fig. 8. Multi-UGV system using two combine harvesters (Iida et al., 2017).

In other words, the state variables of the individual nodes converge to the average of the initial values of the entire node. This state can be explained by the fact that all the node state variables are in consensus. Owing to the consensus, the average of any value held by an individual robot in the MRS is distributed without a centralized computation unit. These properties can be used if the robots are allowed to work while maintaining formations or if an individual node in the network performs the specific tasks it is assigned and interacts with its surrounding nodes to solve a distributed optimization problem.

2.4.1. Multiple UGV

Two types of multi-UGV systems exist: those using conventional agricultural vehicles (Noguchi and Barawid, 2011; Emmi et al., 2014) and those that utilize numerous small-sized mobile platforms (Blender et al., 2016). Most conventional agricultural vehicles are large platforms used in a wide farming area. Using conventional agricultural vehicles for a multi-UGV system is effective when farming a wide area. Furthermore, it ensures superior performance in agricultural tasks (Fig. 8). The performance of agricultural tasks in MRSs based on small- and medium-sized mobile platforms may be inferior; however, owing to their lighter weight and better positioning accuracy, these systems can ensure improved safety and reduced soil compaction.

A study Johnson et al. (2009) demonstrates the implementation of multiple tractors for autonomous peat moss harvesting. In particular, the authors proposed the path planning of three tractors for harvesting operations using two methods. In Zhang et al. (2016), multitractor systems were developed using a leader–follower-based approach for improved operating efficiency. The proposed system successively operated safely in the same region and the work efficiency was 95.1% more than that obtained using a single tractor. However, multiple tractor systems have limitations, according to field conditions; therefore, efficiency cannot always be guaranteed.

Mobile agricultural robot swarms (MARS) for autonomous missions using a coordinated fleet of robots have been proposed (Blender et al., 2016). This approach, which utilizes a mobile robot team, instead of a heavyweight tractor, has the main advantages of scalability and reliability. Moreover, the system incorporates a 40-kg robot to seed with a seeding unit and RTK-GNSS system, and the platform can minimize soil compaction and waste of resources.

2.4.2. Multiple UAV

Owing to the short flight times and low payloads of UAVs, which are critical limitations, the development and application of multi-UAVs are essential in an expansive agricultural environment (Mammarella et al., 2021). Multi-UAV systems are important in practical applications because they are more efficient and incur lower battery costs considering shorter flight times (Skobelev et al., 2018). Furthermore, multi-UAV systems can generally be applied to remote sensing, mapping, and

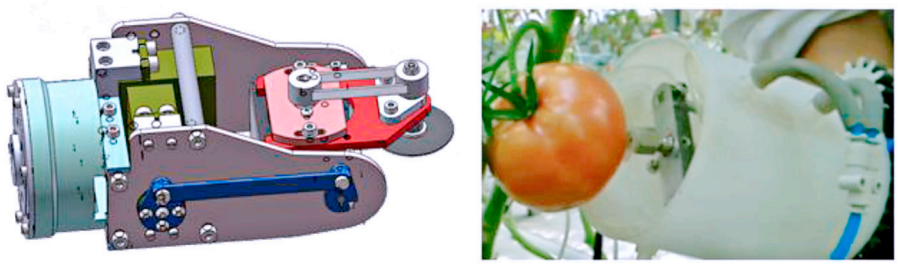


Fig. 9. Two different types of end-effectors. Left: saw cutter type; Right: gripper type (Zhao et al., 2016).

spraying in a wide range of fields (Trianni et al., 2016; Ju and Son, 2018b).

In Barrientos et al. (2011), a task administrator that automatically created sub-area partitions for a team of UAVs based on negotiations among these vehicles by considering their capabilities and state was presented. The authors presented a task scheduler to segment the global desired region into N nonoverlapping subtasks for N UAVs. This procedure for segmenting the area is based on a negotiation process in which the area covered by each UAV is maximized. The UAVs communicate with the base station, feedback their state, and perform coverage tasks in each subarea. A multi-UAV system using teleoperation for agricultural tasks has been developed (Ju and Son, 2019a). In the system, three quadcopters were used for a remote sensing task. The experiment results showed higher performance efficiency for a given agricultural task in the case of their proposed multi-UAV system. In addition, Trianni et al. (2016) introduced the SAGA concept for monitoring and mapping weeds in a field using multi-UAVs. Their strategy was efficient against patchy weed distribution and exhibited decent scalability with the size of the UAV group (10, 50, and 100 quadcopters).

2.4.3. Multiple manipulator

The task allocation of multiple manipulators can be based on either weak (Zion et al., 2014; Mann et al., 2016) or strong cooperation (Zhao et al., 2016; Tanner et al., 2001). The weak cooperation of multiple manipulators is used to harvest only the crops that each manipulator is responsible for when harvesting in the same area. Manipulators that are close to each other must share their positions to prevent collisions while performing their respective tasks. The strong cooperation of multiple manipulators indicates that multiple manipulators carry a single product or work together when harvesting a single crop. Studies on strong cooperation are gaining attention owing to the limited weight-lifting capacity of single manipulators.

In Mann et al. (2016), the authors developed methods to optimize the performance of multiarm 3DOF Cartesian harvesting robots for melon harvesting. The allocation of melons to be harvested by each manipulator to obtain the maximum harvest yield was developed to design an optimal number of manipulators. Based on the motion of 3DOF manipulator, an algorithm was developed based on a color-dependent interval graph to solve the maximum robotic harvest problem. The developed algorithm yielded a rigorous optimal solution and only required information on one fruit to be harvested because of the greedy algorithm. However, owing to 3DOF, it can only perform simple tasks, making it unsuitable for unstructured agricultural environments.

A dual-arm robot for harvesting tomatoes was proposed to improve the efficiency of harvesting robots in unstructured environments (Zhao et al., 2016). A dual-arm-based harvesting robot consists of 3DOF manipulators and each manipulator equipped with two different types of end-effectors (cutter and gripper) was used to harvest a single tomato with strong cooperation (Fig. 9). The gripper-type end effector, which is configured with vacuum suction, grips tomatoes to prevent movement, which makes it easy to cut the tomato stem. As the gripper grasps the tomato, the saw-cutter-type end-effector cuts the tomato stem. This cooperation of the two different types of end-effectors improves the harvesting efficiency and compensates for the limitation of 3DOF manipulator motion.

2.4.4. Heterogeneous multirobot system

Although agricultural MRSs make for increased productivity, heterogeneous MRSs must be introduced for agricultural use to realize more innovative farming in the future (Vu et al., 2018). Heterogeneous MRSs can cooperate with other types of platforms such as UGVs and UAVs (Fig. 10), as well as those of type, which are either different models or similar models with different specifications (e.g., size, speed, and payload). Heterogeneous agricultural field robots are gaining considerable attention because they can efficiently accomplish various agricultural tasks (Doering et al., 2014; Menendez-Aponte et al., 2016; Walter et al., 2018; Bhandari et al., 2017). As with homogeneous MRSs, heterogeneous MRSs are generally modeled based on graph theory (Davoodi et al., 2020; Ronzhin et al., 2022).

In Conesa-Muñoz et al. (2016), a heterogeneous MRS comprising UGVs and UAVs was proposed. The UAVs were used to gather environmental information, which the UGVs used to perform interventions more efficiently. In particular, the UAVs monitored the crop and created an accurate weed patch map that was subsequently used for planning tasks for the UGVs. The station computer used the mission manager to determine the mission to be performed by the UAVs and UGVs. The mission manager automated tasks using a higher layer built on lower-level operations performed by the UGVs and UAVs.

In Potena et al. (2019), cooperation between a UGV and UAV was proposed for constructive mapping. A four-wheeled mobile platform and quadcopter were used with onboard cameras to gather color point clouds for mapping. Although UAVs can rapidly map wide areas, the image resolution is often poor. To compensate for this, Potena et al. first mapped the environment using a UAV and then the UGV reached the selection area and updated the precise map. Experiments were performed to compare the robustness of the proposed method to that of the conventional method.

In Barrientos et al. (2011), research on collaboration within the same platform for various models was considered. Using two different models, they employed three UAVs for aerial remote sensing in agriculture. The two payloads, weights, and diameters of the two types of UAVs were different. For heterogeneous MRSs, their sub-region division and task decomposition methods for collaboration considered the capabilities of individual UAVs, which is a helpful feature.

3. Controls

To apply MRS in various fields of agriculture (Lytridis et al., 2021), numerous core technologies are required to ensure scalability and performance. For example, elements such as localization (Bayar et al., 2015), perception, mapping (Egger et al., 2018), obstacle avoidance (Ball et al., 2017), motion control (Noguchi et al., 2004), task decomposition and allocation, path planning, coordinated control, and cooperative control must be integrated organically. Therefore, a detailed review from the viewpoint of MRS control is conducted in this

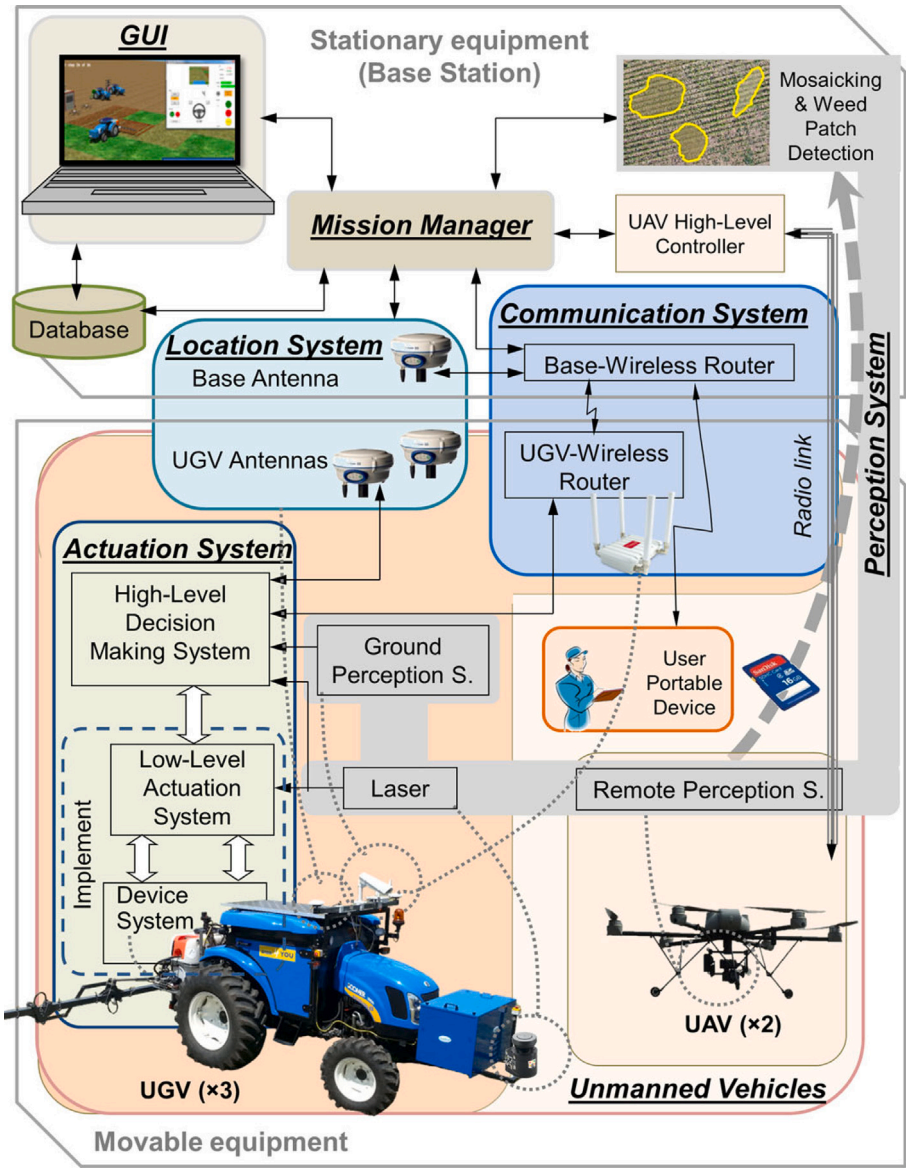


Fig. 10. Heterogeneous MRS architecture for weed and pest control (Gonzalez-de Santos et al., 2017).

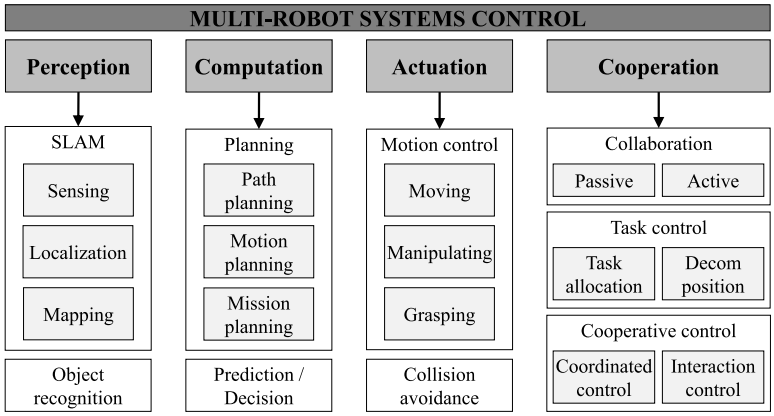


Fig. 11. Classification of multirobot systems control.

section and general algorithms are described. The technologies required for MRS control can be grouped according to various perspectives; however, in this study, we categorized them as perception, computation, actuation, and cooperation, as shown in Fig. 11. Consequently, the control of a single robot and that of MRSs based on these classifications are comprehensively reviewed.

First, the control of the cooperation of the MRS divides the main task into subtasks according to the number or ability of the robots. These controls are called "task decomposition", and subtasks are assigned to multiple robots (Khamis et al., 2015). The control methods, which are being studied as cooperative control or swarm control, can either be passive or active collaboration, according to the interactions of MRSs (Rizk et al., 2019; Dias et al., 2021). For example, passive collaboration consists of task allocation and path planning, and active collaboration includes coordination (Yan et al., 2013) or interaction control (Tuci et al., 2018; Feng et al., 2020; Farivarnejad and Berman, 2021) such as formation control and cooperative manipulation.

The MRS control architecture can be designed based on the centralized, decentralized, or distributed approaches, based on considerations such as network connection, robot interaction, and system stability. In Nebot et al. (2011), a distributed control architecture for a heterogeneous MRS responsible for the maintenance of agricultural environments was introduced. The architecture considered performance aspects such as scalability, data distribution, and hardware abstraction. For centralized control-based passive collaboration, Nebot et al. developed a sense-act system of heterogeneous MRS for task automation in large outdoor areas. The proposed control method processed the workflow of a task based on information sharing between the UAV and UGV. Several studies have been conducted on the control of agricultural homogeneous/heterogeneous MRSs (Vu et al., 2017; Carbone et al., 2018). Thus, the focus in this section is on the control perspective.

3.1. Low-level control for single robot

To apply MRSs, a single robot must individually recognize its surrounding environment and perform the desired motion while avoiding collisions. Therefore, low-level control of a single robot is guaranteed and stabilized. In particular, the motion control and obstacle avoidance of agricultural robots are being studied in general (Cheein and Carelli, 2013; Bechar and Vigneault, 2016, 2017; Gao et al., 2018b; Fountas et al., 2020). As an optimal method for controlling a single robot, Timo Oksanen & Arto Visala (Oksanen and Visala, 2009) solved the coverage path planning problem in agricultural fields using greedy and incremental algorithms. The developed control system using trapezoidal decomposition and incremental algorithms showed improved planning performance by selecting the best driving directions and subfields based on the current state of the robot. However, they did not solve the path-planning problem optimally.

In Bergerman et al. (2015), a control system capable of supervision by teleoperating the agricultural vehicle at a ground station was constructed. Bergerman et al. used a pure pursuit controller to allow UGVs to follow the centerline between trees in an orchard. They designed three control methods for mule, scaffold, and pace modes to allow orchard vehicles to drive autonomously in different situations. The proposed navigation system using GPS and laser scanner-based localization includes features such as row-following, end-of-row detection, obstacle detection, rotation, and new-of-row entry. However, technical challenges such as model-based controllers, real-time control, and integration of control modes are still encountered.

Similarly, Ball et al. (2016) developed a vehicle control system consisting of novelty-based obstacle detection, visually aided localization, a coverage planner, and collision-free navigation. The probability density was estimated to detect novelty, which is defined as $p(x) \approx \frac{1}{\sum_i w_i} \sum_i w_i k_\sigma \left(x - x_i\right)$, where $p(x)$ is the probability density at query point x, w_i is the weight of sample x_i, and $k_\sigma(x)$ is the Gaussian kernel function with a width parameter σ. Particle-filter-based sensor fusion and boustrophedon decomposition were applied for localization and coverage planning, respectively. Finally, they developed a cost-map-based global and local planner using a robot operation system for navigation and controlled a mobile robot through professional-integral-feedforward in the low-level domain.

For optimal control, in Guan et al. (2021), tracking algorithms and strategies were studied to reduce navigation path tracking errors. A circular arctangent line tracking model and fuzzy control-based hydraulic steering actuator controller were proposed for the auxiliary navigation system. Furthermore, to create a functional link between the yaw rate, control variable, and rectifying control errors owing to slippage and crawler sinking, a least-squares support vector machine regression-based steering feature identification approach was presented. To improve agricultural production efficiency, low-level control systems of single robots, which must be guaranteed to configure MRSs, are continuously being studied.

3.1.1. Motion control

Noguchi et al. (2004) proposed GOTO and FOLLOW for the motion control of the master–slave MRS. GOTO is a control algorithm in which the master robot commands the slave robot to drive itself from its current operational position to specified positions. FOLLOW is an algorithm that achieves collaboration by controlling the slave to maintain a predetermined relative distance and angle with the master robot, irrespective of the driving speed and direction. A nonlinear sliding mode controller was applied to ensure robustness, in terms of lateral offset and spacing control. In the experiments, the proposed system outperformed a typical PD controller in terms of robot motion control.

In another method, Bayar et al. (2015) enhanced the path-following performance by calculating the velocity v_c and steering instructions ϕ_c using the robot's motion model, which incorporated the effects of the wheel sideslip, as illustrated in Fig. 12. The controller receives the desired path from the path generator as input. Laser data were utilized to extract the support lines of a row of trees and the vehicle's distance and direction relative to the trees in front for vehicle localization. Consequently, the model-based controller received lateral and orientation errors about the desired path. The controller was evaluated through field tests, i.e., by comparing it with a pure pursuit controller. Based on the findings, the proposed method exhibited superior path tracking performance. They used a laser for localization; however, if they had used either odometry or IMU, the tracking performance would have estimated a more accurate position.

For a manipulator system, Bac et al. (2016) proposed a constrained-azimuth strategy that avoided dangerous pathways while achieving successful motion planning comparable to the full-azimuth method. To assess the effectiveness of their collision-free pathfinding, a sensitivity analysis was performed for five factors describing the crop (stem spacing and fruit placement), robot (end-effector size and robot position), and planning method.

3.1.2. Obstacle avoidance

In Bac et al. (2016), a collision detection method was designed based on the distance calculations between the form primitives characterizing the manipulator and end-effector, stem segments, wires, and fruit to construct a collision-free route. Each link was modeled as a boundary box (Fig. 13) to detect collisions between the manipulator and end effector. As mentioned in Section 3.1, collision-free path planning and smoothing algorithms were applied to a harvesting robot based on a rapidly exploring random tree. The experiment results revealed a reliable goal configuration, even in a dense crop environment.

For collision avoidance in mobile robots, Ball et al. (2017) developed a vision-based obstacle detection system that continuously reflected environmental and lighting variations. They utilized a novelty-based obstacle detector (Ross et al., 2015) to distinguish prospective barriers using the selective focus approach in image space. The proposed approach had fast computing time; however, it was unable to detect camouflaged objects. To address this issue, a combined appearance and structure obstacle detector was studied.

Similarly, Skoczeń, et al. proposed an RGB-D camera-based perception system in Skoczeń et al. (2021). The system was constructed

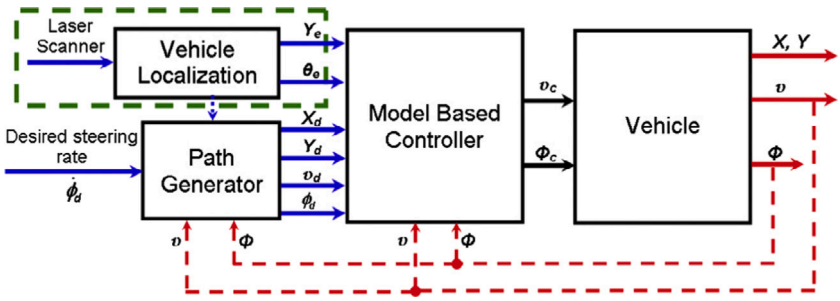


Fig. 12. Model-based control architecture of the agricultural vehicle (Bayar et al., 2015).

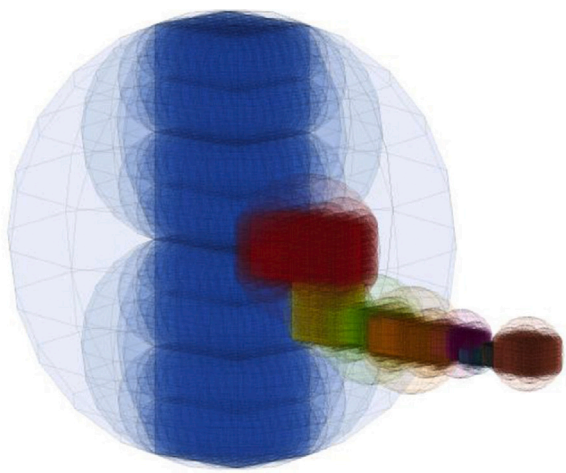


Fig. 13. Representation of bounding box for the manipulator with octrees of spheres (Bac et al., 2016).

through semantic RGB image segmentation, labeled point cloud reconstruction, and obstacle mapping processes. The cost-map layer, which represents the occupancy grid, was built to incorporate the output of the perception system into the navigation module.

3.2. Localization and mapping

For robots to navigate and function, their localization, which is required to identify the robot's position, and mapping, which helps establish the environmental information, are crucial technologies from the control viewpoint. Therefore, simultaneous localization and mapping (SLAM) is essential for control functions such as autonomous driving, obstacle avoidance, and MRS cooperation (Bechar and Vigneault, 2016; Imperoli et al., 2018). The literature on the SLAM of a single robot and MRS is reviewed in this section.

A precise localization system using a high-cost real time kinematic (RTK)-GPS was utilized in Cheein and Carelli (2013), such that the position error of the field robot was within several centimeters. However, the positioning accuracy of standard GPS sensors is low owing to problems such as communication and satellite locking. RTK-GPS systems are expensive and lack practical efficiency in agricultural environments (Ball et al., 2017). Therefore, sensor fusion using low-cost sensors and various filtering algorithms has been studied. However, for more precise localization, Ball et al. used a sensor fusion of RTK-GPS, wheel geometry, and IMU.

Bergerman et al. (2015) solved the two-dimensional pose estimation problem by predicting the location and heading of the vehicle using the extended Kalman filter (EKF) framework for localization of the orchard platform. In the first step, the pose was predicted using odometry from the wheel and steering encoders. Then, the processed laser points were used for row and landmark detection to update the estimated robot pose. The perception system used GPS-free sensors; however, it was unsuitable for online-based localization and mapping. Similarly, in Bayar et al. (2015), steering and wheel encoders and laser rangefinders were used to estimate the vehicle position while driving between the rows of trees.

Ball et al. (2016), RTK-GPS position, wheel odometry, IMU-based yaw rate, and crop row-tracking-based offset and heading were fused using particle filters, as shown in Fig. 14. This approach allows their localization system to traverse for long periods without access to one or more information sources. Recently, Egger et al. proposed an approach using 3D LiDARs for reliable long-term localization in dynamic environments (Egger et al., 2018). They extracted distinctive features from range measurements and bundled them into local views with observation poses to generate *PoseMaps*. A major advantage of the proposed map representation is the simplicity and speed of the map queries. Online map extensions have also been studied, to increase the robustness and versatility of SLAM performance (Le et al., 2019).

For the MRS SLAM, Roldán et al. studied aerial-ground cooperation to map environmental variables in greenhouses (Roldán et al., 2016). The SLAM algorithm employs two references to determine the robot's position: readings from the lasers and the fusion of odometry and IMU data with the EKF. Then, navigation was performed using the previously obtained map and the *augmented Monte Carlo localization* algorithm. Finally, the ground vehicle covered the greenhouse, and environmental variable maps were created. The system used a heterogeneous MRS to assess the humidity, temperature, carbon dioxide concentration, and luminosity at various heights.

3.3. Passive collaboration

The significant studies of passive and active cooperation of agricultural MRS are summarized in Table 1. Passive collaboration mainly results in task decomposition, allocation (Barrientos et al., 2011; Rossi et al., 2015; Seyyedhasani and Dvorak, 2017; Gao et al., 2018a; Seyyedhasani et al., 2019; Elmokadem, 2019; Kiktev et al., 2020; Cao et al., 2021; Edmonds and Yi, 2021; Harman et al., 2021; Davoodi et al., 2021), and path planning (Johnson et al., 2009; Barrientos et al., 2011; Conesa-Muñoz et al., 2012; Lal et al., 2017; Blender et al., 2016; Seyyedhasani et al., 2019; Filip et al., 2020; He et al., 2020; Fayaz et al., 2021; Vahdanjoo and Sorensen, 2021; He and Li, 2021; Wang et al., 2021b; Miao et al., 2021) problems for MRSs (Nolan et al., 2017; Hameed, 2018; Faryadi et al., 2019). The path planning of MRSs, consisting of a single robot team, has been expanded from existing problems (Moysiadis et al., 2020; Santos et al., 2020). In this section, the passive cooperation between homogeneous and heterogeneous MRSs is described.

Barrientos et al. proposed a single-phase automatic task decomposition based on negotiation, considering the conditions and capabilities of the MRS (Barrientos et al., 2011). When multiple robots are assigned subtasks, the optimum path-planning method determines the route to be followed by each robot. Furthermore, robust flight control has been developed to improve the maneuverability of UAVs.

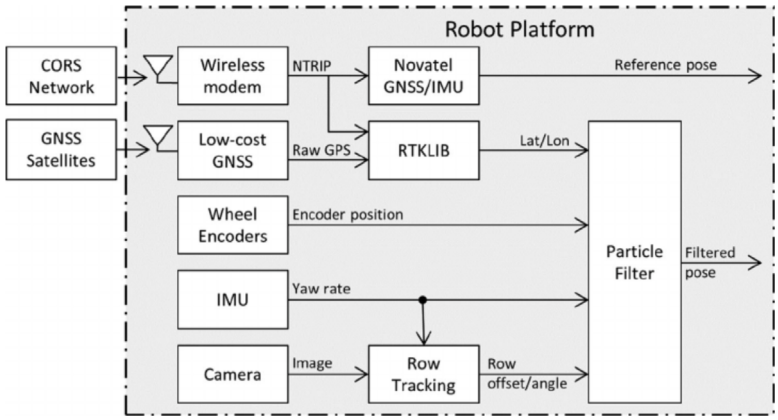


Fig. 14. Overview of the localization system (Ball et al., 2016).

Table 1
Controls of agricultural multirobots.

Objectives	Platforms		Controls				Ref
Area coverage	Homo-geneous	UAVs	Passive	Negotiation-based one-phase task partitioning	Cost-based optimal path planning	Backstepping and Frenet–Serret theory	Rossi et al. (2015)
Manipulation	Homo-geneous	Manipulators	Active	Human–robot interaction-based cooperation	Artificial recognition approach	None	Zhao et al. (2016)
Mission planning	Hetero-geneous	UAV–UGV	Active	Model-based mission control	A* and numerical approximation	ROS navigation	Roldán et al. (2016)
Mission planning	Hetero-geneous	UAV–UGV	Active	Minimum and maximum radii of input disks-based approximation		Waypoint following control	Tokekar et al. (2016)
Area coverage	Homo-geneous	Robots	Active	Local information-based task allocation and coordination		None	Janani et al. (2016)
Mission planning	Hetero-geneous	UAV–UGV	Active	Mission manager	Decision control algorithm	PID	Gonzalez-de Santos et al. (2017)
Mission planning	Homogeneous	UAVs	Active	Multi-objective-based mission planning using Genetic Algorithm and Particle Swarm Optimization		Minimum turning radius-based control	Zhai et al. (2018)
Area coverage	Homo-geneous	UGVs	Passive	Dynamic programming for D*	Cost-based optimal path planning	Waypoint following control	Gao et al. (2018a)
Area coverage	Homo-geneous	UGVs	Active	Distributed density function-based partitioning	Energy-aware control policy	None	Davoodi et al. (2018)
Area coverage	Homo-geneous	Robots	Active	Improved greedy partial row heuristic	Vineyard Sectioning	None	Thayer et al. (2018)
Area coverage	Homo-geneous	UAVs	Passive	Voronoi partitioning	Sliding mode control-based distributed control		Elmokadem (2019)
Area coverage	Homo-geneous	Robots	Passive	Modified Clarke–Wright algorithm (heuristic)	Tabu search (meta-heuristic)	None	Seyyedhasani et al. (2019)
Area coverage	Homo-geneous	Robots	Passive	Graph transformation and mixed integer linear programming-based planning		None	Lal et al. (2017)
Task planning	Homo-geneous	Robots	Passive	Finite state machines-based task planning and control		None	Kiktev et al. (2020)
Area coverage	Hetero-geneous	Robots	Active	Mixed time- and energy-based Voronoi partitioning	Distributed deployment strategy	None	Faryadi and Moham-madpour Velni (2021)
Task allocation	Homo-geneous	Robots	Passive	Improved ant colony algorithm-based static and dynamic assignment		None	Cao et al. (2021)
Coordination	Hetero-geneous	UAV–UGV	Active	Hybrid state automata-based task planning and control		Distributed swarm control	Ju and Son (2021a)
Task allocation	Homo-geneous	UGVs	Passive	Kernel-based Gaussian process machine learning	Geodesic Voronoi region	None	Edmonds and Yi (2021)
Coordination	Heterogeneous	UGVs	Active	Position-based dual master–slave mode control	Cloth simulation filter and random sample consensus algorithm	Pure pursuit algorithm	Mao et al. (2022)

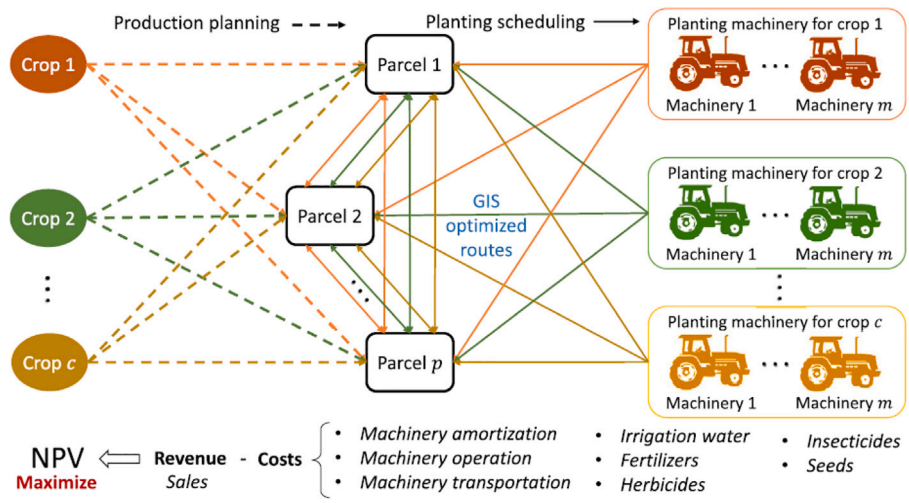


Fig. 15. Structure of developed model (Vazquez et al., 2021).

In Valente et al. (2013), a strategy for optimizing the cost variable was proposed to address the MRS route planning by reducing the number of turns. The proposed method employed a metaheuristic algorithm inspired by the delightful harmonic improvisation of jazz musicians. Another way of combining a hierarchical planning approach and decision-making is through a collection of agricultural robots that cooperate on specific farming chores such as citrus harvesting (Li et al., 2015). A reconfiguration event and cooperative route-planning algorithm based on a local pursuit approach were proposed to provide optimal trajectories for the MRS within the algorithm framework.

Conesa-Muñoz et al. proposed an approach to optimize the route planning of MRSs by considering the flight distance, time, input costs, robot features, field variability, and refilling possibilities. The results indicated that the proposed system tackled an agricultural case and the optimal route was significantly variable, depending on the characteristics of the robots, variability of fields, and optimization criteria. The MRS refill scheduling problem was also addressed in D'Urso et al. (2018), proving the robustness against inaccuracy in predicting the resource usage rate.

Cobbenhagen et al. addressed the problem of allocating multiple resources to a heterogeneous MRS over time such that the robots can achieve results while maximizing a profit function defined as (Cobbenhagen et al., 2018)

$$J_\iota = \mathbb{E}\left\{\sum_{j\in\mathcal{M}}\left(\pi^\top x_T^j - \sum_{t=\iota}^{T-1}\left(\rho^\top u_t^j + \sigma^\top\left[A_t\right]_j\right)\right)\right\} \tag{7}$$

where $A_t \in \mathbb{N}_{[0,q]}^{n\times m}$ is the allocation matrix, and $\left[A_t\right]_{ij}$ denotes the number of times Agent $i \in \mathcal{N}$ serves Client $j \in \mathcal{M}$ between time t and $t+1$. The decision variables were the amount of delivered resources u_t^j for all $t \in \mathbb{N}_{[\iota,T]}$ and all $j \in \mathcal{M}$ and the allocation of agents and clients $\left[A_t\right]_{ij} \in \mathbb{N}_{[0,q]}$ for all $t \in \mathbb{N}_{[\iota,T]}$. The proposed system utilizes decomposition in which the cost objective is additive for large-scale MRS resource allocation.

As previously described, passive collaboration of MRSs focuses on optimization based on the cost function. Recently, task allocation, decomposition, and planning studies, such as the optimal schedule for harvesting robots (He et al., 2019), optimal scheduling and sequencing for seeding robots (Ahsan and Dankowicz, 2019), and optimal production planning and scheduling for planting robots (Fig. 15) (Vazquez et al., 2021) have been reported. In another method, an artificial potential field approach to MRS full coverage path planning was studied to achieve spontaneous organization and coordination of multiple robots (Miao et al., 2021).

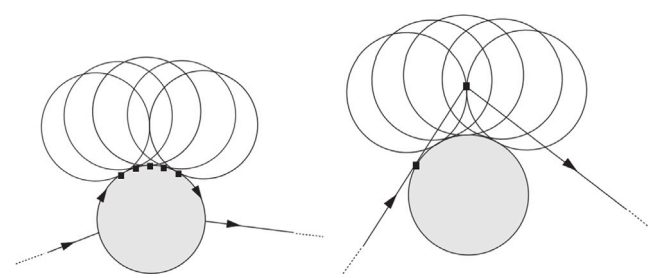


Fig. 16. Concept of proposed model (Tokekar et al., 2016).

The leading robot or centralized control center decomposes the global task and transmits the subtasks to each robot according to the proper allocation strategy in passive cooperation. Therefore, the control system has the advantage that each subtask determines the appropriate robot to perform it, and the robot system to perform the overall task.

3.4. Active collaboration

Active collaboration mainly results in task division, allocation (Roldán et al., 2016; Tokekar et al., 2016; Janani et al., 2016; Gonzalez-de Santos et al., 2017; Davoodi et al., 2018; Thayer et al., 2018; Zhai et al., 2018; Lujak et al., 2020; Faryadi and Mohammadpour Velni, 2021), path planning (Zion et al., 2014; Conesa-Muñoz et al., 2015; Mann et al., 2016; Faryadi et al., 2020; Mammarella et al., 2020), leader–follower control (Noguchi et al., 2004; Emmi et al., 2014; Chevalier et al., 2015; Zhang et al., 2016; Thomasson et al., 2018; Mao et al., 2022), formation control (Emmi et al., 2014; Chevalier et al., 2015; Zhang and Noguchi, 2017; Guillet et al., 2017; Tourrette et al., 2018; Ju and Son, 2018b, 2019a,b, 2021b; Teslya et al., 2021; Ju and Son, 2021a), and cooperative manipulation problems (Zion et al., 2014; Mann et al., 2016; Zhao et al., 2016; Ahlin et al., 2017; Edmonds, 2022). Active collaboration is being studied for more complex control systems because, unlike passive collaboration, it entails direct communication or interaction between robots.

For example, the control of the MRS, which forms a formation for harvesting or carrying harvested crops together, is considered an active collaboration (Thomasson et al., 2018; Ju and Son, 2018a; Edmonds et al., 2021). In Tokekar et al. (2016), an approximation technique for the sampling traveling salesman issue, which involved selecting a sampling site on each disk and a tour to visit the sampling locations to reduce the total travel and measurement durations, was

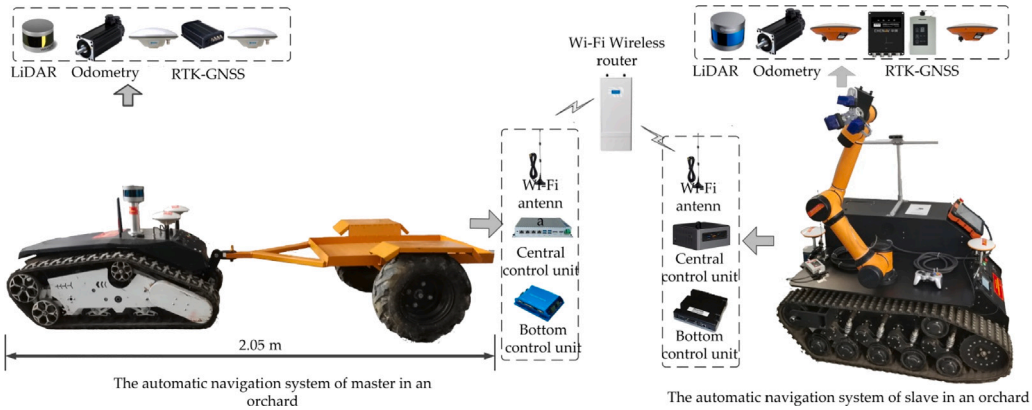


Fig. 17. Hardware structure of MRS (Mao et al., 2022).

provided(Fig. 16). Active collaboration of the MRS was demonstrated through scenarios in which the UAV landed on the UGV, which then transported it.

In Zion et al. (2014), algorithms were proposed to plan the allocation of harvesting melons by each arm in an active cooperative manner such that a given number of robots can harvest the maximum number of fruits. Therefore, optimal task allocation was developed by applying greedy and approximation algorithms to generate optimal solutions for subgraph problems. The control algorithms were designed to facilitate the economic optimization of the design of such robots based on the labor cost, value of the crop, costs of robotic arms, and operation time. In another method (Gonzalez-de Santos et al., 2017), a heterogeneous MRS with decision-control algorithms was designed to decrease pesticide use and safeguard the environment while maintaining sufficient food production. This study was aimed at designing, developing, testing, and evaluating the MRS for effective pest and weed management, reducing pesticide inputs, and improving producer health, crop quality, and safety.

Wenju et al. devised a dual master–slave system based on leader–follower control (Fig. 17) to address the problem of navigation in agricultural harvesting equipment that cannot repeatedly break between winding drives and rows of trees (Mao et al., 2022). Based on the distance obtained from the global positioning system (GNSS), the navigation mode of the transport and picking robots was changed using ground points based on the distance obtained from the global positioning system. To compute the slave turn-way point, the GNSS point was manually selected as the master waypoint. They eventually employed pure pursuit algorithms to follow these sites consecutively to accomplish the master–slave navigation.

Active collaboration in MRSs is essential for the complete automation of agricultural tasks, and more studies are required on challenges such as cooperative manipulation-based transportation, harvesting, and diagnosis. Robots in the active task allocation method do not have global awareness of their tasks; however, they compute and plan independently based on the localization provided by their local sensors. The performance of each robot is directly tied to the combined impacts of these agents, which determine the overall performance of the system.

4. Applications

As the effectiveness of robots in agricultural fields have been demonstrated (Mahmud et al., 2020), studies on the efficient utilization of multirobots for various applications to cover large fields have gained popularity (Aravind et al., 2017). In this section, the applications of multirobot agriculture, which are summarized in Tables 2 and 3, are presented.

4.1. Mapping and remote sensing

Remote sensing is a means of obtaining field information. It is commonly performed using UAVs with a location sensor (GPS) along a designated path. Two- or three-dimensional maps can be created using remote-sensing aerial imagery. Maps of an agricultural field can provide useful information such as soil conditions (Pulido Fentanes et al., 2020), status, location and growth of weeds, and crop status. However, a single UAV cannot easily map wide fields owing to its low battery capacity. Therefore, several studies have been conducted to perform mapping using multiple UAVs (Barrientos et al., 2011; Trianni et al., 2016; Albani et al., 2017b; Chao et al., 2008).

In Ju and Son (2018b), a multi-UAV system was developed for agriculture by using the remote control of a distributed swarm algorithm. A 3-DOF haptic device was used to control the UAVs simultaneously (Fig. 18 (a)). They compared the performance of single and multiple UAVs, autonomous control, and remote control using several experiments. The experiment was divided into cases consisting of *auto-single-UAV, auto-multi-UAV, tele-single-UAV* and *Tele-Multi-UAV*. According to the experiment results, the performance of *multi-UAV* is superior to that of *single-UAV*.

A heterogeneous MRS may include both UGV and UAV and can be deployed for mapping for flexibility, which improves the system performance. In Potena et al. (2019), a method for effectively aligning heterogeneous 3D maps was proposed by solving the problem of cooperative UAV–UGV environmental reconstruction in agricultural scenarios, as shown in Fig. 18(b). They proposed *AgriColMap*, a novel map that leverages a grid-based multimodal environment representation that uses the geometry and semantics of the target field. Furthermore, they reported a comprehensive set of tests that demonstrated the robustness of their approach in comparison to conventional methods.

Roldán et al. (2016) proposed a heterogeneous MRS to measure the environmental variables in greenhouses. The proposed MRS monitored the environmental conditions of crops (e.g., humidity, temperature, carbon dioxide, and luminosity). When the UAV and UGV cooperated, the UAV was required to move about in search of the source of the error when the UGV acquired anomalous measurements according to the designed system. Furthermore, if a UGV detected an unavoidable object, the UAV must continue its path planning. The simulation results demonstrated that the intervention of aerial robots could potentially improve performance.

4.2. Seeding

Seeding is a fundamental and essential task in agriculture and has long been mechanized using tractors because it requires considerable labor. However, in a wide range of fields, the use of only one tractor

Table 2
Applications of agricultural multirobots.

Task	Homo/ Hetero	Platform/ (number of robots)	Sensors	MRTA	Connectivity	Objective	Environment	Crop	AdditionalTask	Ref
Remote sensing	Homo	UAV-quadcopter (3)	RGB camera, IMU, GPS	ST-MR-TA	Distributed	To develop a multi-UAV system for agriculture with teleoperation using the haptic device	Outdoor	All crops	Mapping	Ju and Son (2018b)
	Hetero	UAV-quadcopter (3)	IMU, GPS, X-bee	ST-SR-IA	Centralized	To develop a team of UAVs that can capture georeferenced pictures to create a full map	Outdoor	Vine	Mapping	Barrientos et al. (2011)
		UAV-quadcopter (1) UGV-4WD (1)	Temperature/humidity/luminosity/ carbon dioxide concentration sensor, ultrasonic altimeter, RGB camera, IMU, GPS, laser scanner	MT-MR-TA	Centralized	To map the environmental variables (temperature, humidity, luminosity, and CO_2 concentration) of greenhouse	Greenhouse	All cropsin greenhouse	Mapping	Roldán et al. (2016)
Seeding	Homo	UGV-4WD (6)	IMU, GPS	ST-SR-TA	Centralized	To perform seeding using multirobots with minimum sensor technology to realize a low-cost and energy -efficient system that provides scalability and reliability	Outdoor	All crop seeds	-	(Blender et al., 2016)
Weed detection	Homo	UAV-quadcopter (10, 50, 100)	Ultra-wideband (UWB), GPS, RGB camera, IMU	ST-MR-TA	Distributed	To reduce pesticide input and preserve the environment, while maintaining the necessary level of food production	Simulation	Lettuce	Mapping	Trianni et al. (2016)
	Hetero	UAV-quadcopter (2) UGV-4WD (1)	Infrared camera, RGB camera, 4-channel camera, GPS, IMU, LiDAR, Zigbee	MT-MR-TA	Centralized	To develop a combined system that allows performing autonomous weed detection and spraying tasks in large outdoor areas by integrating heterogeneous types of platforms in a fully automated manner	Outdoor	Cereal	Mapping, Spraying	Conesa-Muñoz et al. (2016)
		UAV-quadcopter (2) UGV-4WD (1)	RGB camera	ST-MR-TA	Distributed	To develop MRSs and collaborative approaches as potential solutions to improve efficiency and system robustness	Outdoor	Sugar beet,Potato	Mapping	Albani et al. (2017a)
Spraying	Homo	UGV-2WD (20~100)	RGB camera	ST-MR-TA	Distributed	To propose a cooperative strategy by which a team of robots can perform spraying over a large field	Simulation	All crops	–	Janani et al. (2016)
	Hetero	UGV-4WD (2)	UWB, GPS, Lidar	ST-MR-IA	Decentralized	To develop a spraying system based on UWB technology for the formation control of a mobile robot following a leader robot	Outdoor	Vine	–	Tourrette et al. (2018)
		UAV-quadcopter (2) UGV-4WD (3)	GPS, RGB camera, Laser, ultrasonic sensor	ST-MR-IA	Decentralized	To develop robotic systems for effective weed and pest control aimed at reducing the use of agricultural chemical inputs	Outdoor	Wheat, Olive,Cereal	Weed detection	Gonzalez-de Santos et al. (2017)

Table 3
Applications of agricultural multirobots.

Task	Homo/ Hetero	Platform/ (number of robots)	Sensors	MRTA	Connectivity	Objective	Environment	Crop	AdditionalTask	Ref
Fertilization	Homo	UGV-3WD (20 - 203)	Sensors not specified	MT-MR-IA	Centralized	To develop a fertilizing system using MRS as robots can easily drive between the rows of corn and target the nitrogen fertilizer directly at the base of each plant	Simulation	Wheat	Weed removing, Spraying	Minßen et al. (2011)
Phenotyping	Homo	UGV-Tracked vehicle (3)	RGB camera, barometer, gyroscope, GPS, accelerometer, magnetometer	ST-SR-IA	Centralized	To develop lightweight distributed multirobot systems for row crop phenotypic data collection	Outdoor	Soybean	Mapping	Gao et al. (2018a)
	Hetero	UAV-quadcopter (1) UGV-4WD (1)	VIS/NIR multispectral camera, RGB camera, GPS	ST-SR-IA	Centralized	To develop complementary methods for optimal plant analysis by comparing images from UAV and UGV	Outdoor	Wheat	Mapping	Burud et al. (2017)
Irrigation	Hetero	UAV-fixed wing (2), quadcopter (1)	RGB camera, NIR camera, GPS	ST-MR-IA	Centralized	To develop a system of UAVs for cooperative remote sensing for real-time water management and irrigation control using image stitching	Outdoor	Desert lake	Mapping, Remote sensing	Chao et al. (2008)
		UAV-quadcopter (1) UGV-4WD (1)	RGB camera, GPS	ST-SR-IA	Centralized	To develop a system that aims at creating a co-robotic system to implement precision irrigation on large-scale commercial vineyards	Outdoor	Wheat	Mapping, Remote sensing	Thayer et al. (2018)
Harvesting	Homo	UGV-4WD (3)	RGB camera, Infrared camera, Lidar	ST-SR-IA	Centralized	To develop a system of three tractors for coordinated autonomous peat moss harvesting	Outdoor	Peat moss	–	Johnson et al. (2009)
		UGV-4WD (2)	GPS, GNSS, IMU	ST-SR-TA	Distributed	To develop two head-feeding combine harvester robots and perform cooperative harvesting using wireless communication	Outdoor	Rice	–	Iida et al. (2017)
	Hetero	UGV-4WD (1) Manipulator — 3DOF (3~8)	GPS, gray-scale camera	ST-MR-TA	Centralized	To develop a multiarm robotic harvester for melon crop and optimize the number of arms, robot speed, and fruit handling time during the harvest	Simulation	Melon	–	Zion et al. (2014)
		UGV-4WD (1) Manipulator — 2DOF (4~6), 3DOF (4~8)	Sensors not specified	ST-MR-TA	Centralized	To develop a mobile melon robotic harvester consisting of multiple 3DOF manipulators	Simulation	Melon	–	Mann et al. (2016)
		UGV-Carrier type (1) Manipulator — 3DOF (One dual arm type)	Stereo camera	ST-MR-TA	Centralized	To improve the efficiency of robotic harvesting using the modular concept of dual-arm robot with different types of end-effectors (saw cutting type and pneumatic-type gripper) for harvesting tomatoes	Greenhouse	Tomato	–	Zhao et al. (2016)

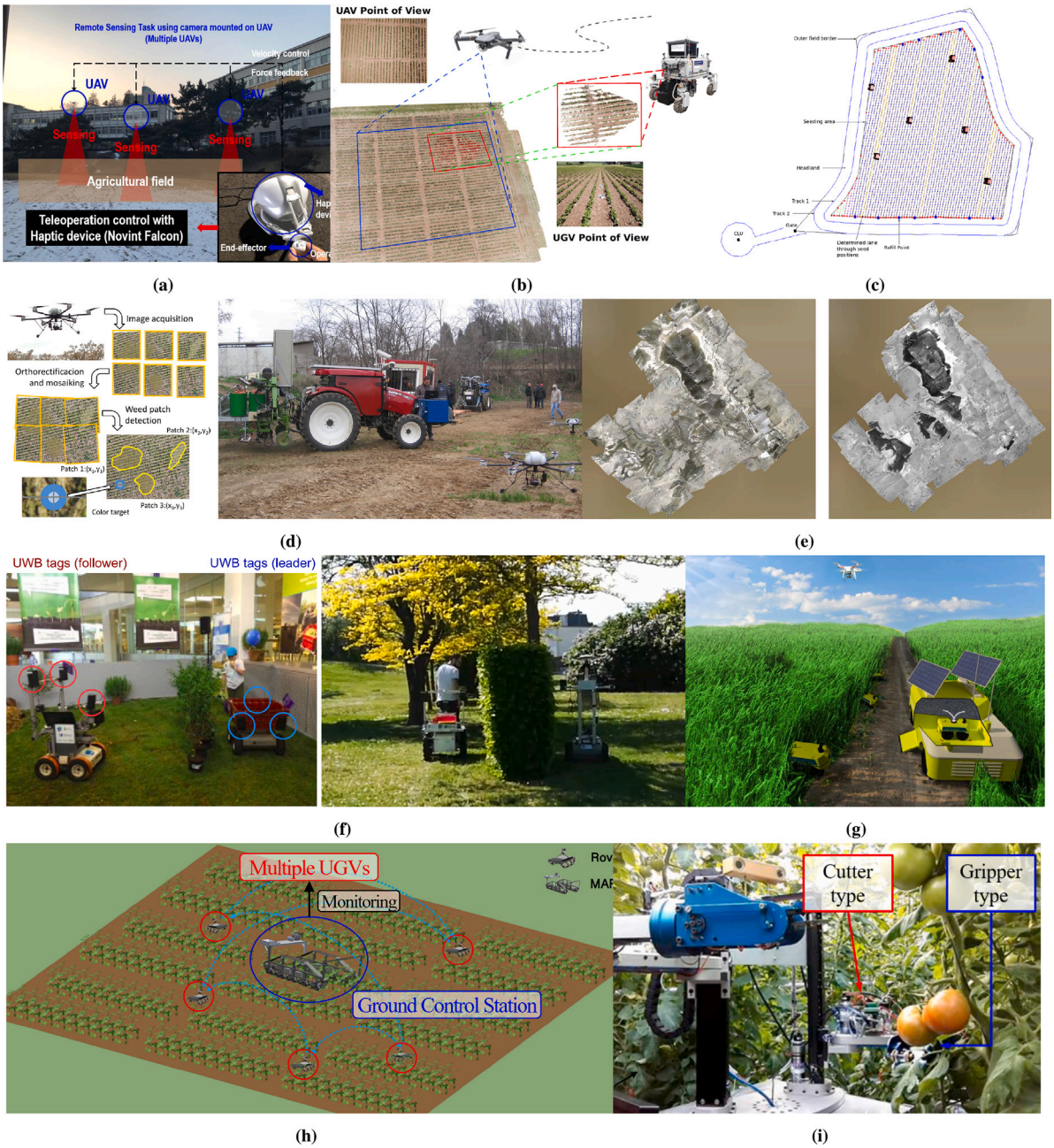


Fig. 18. Various agricultural applications of multirobots: (a) remote sensing (Ju and Son, 2018b); (b) mapping (Potena et al., 2019); (c) seeding (Blender et al., 2016); (d) weed detection (Gonzalez-de Santos et al., 2017); (e) irrigation (Chao et al., 2008); (f) pesticide spraying (Tourrette et al., 2018); (g) fertilization (Minßen et al., 2011); (h) phenotyping (Gao et al., 2018a); and (i) harvesting (Zhao et al., 2016).

still requires considerable effort. In addition, seeding with heavy tractors creates problems such as soil compression. Therefore, the use of multiple lighter robots for seeding is highly effective.

Blender et al. (2016) proposed a MARS approach for autonomous agricultural tasks using the coordinated organization of robots for seeding tasks (Fig. 18(c)). In the system concept, each robot is equipped with a minimum number of sensors to achieve an energy-efficient and low-cost system that provides reliability and scalability. The robot teams are organized by a centralized entity called *OptiVisor*, which performs optimization, path planning, supervision, and control. Practical testing and simulations were performed using the developed robots attached to a high-accuracy positioning system (RTK-GNSS). The simulation considered six robots and testing was performed using two robots to demonstrate the applicability of the system to an actual seeding task.

4.3. Weed detection and spraying

The most significant problem with weeds is that they can interfere with the growth of crops and become habitats or breeding grounds for germs and worms, hence reducing crop quality. In addition, weeds grow faster than crops and possess strong breeding power and a long seed life. Therefore, they can occupy the land and space intended for crops, thereby depriving them of nourishment and moisture. When weeds grow larger than crops, they also block sunlight from reaching the crops and thus interfere with photosynthesis. Therefore, weed removal is an essential task in agriculture (McAllister et al., 2022), and it is necessary to develop technologies for weed detection (Albani et al., 2017a; Conesa-Muñoz et al., 2016; Zhang et al., 2021) and spraying pesticides (Lal et al., 2017; Minßen et al., 2011; Kim et al.,

2020b; Seol et al., 2021). For weed detection, Drenjanac et al. (2013), Gonzalez-de Santos et al. (2017) proposed the Robot Fleet project for highly effective agricultural and forestry management (RHEA), with the goal of designing automatic weed mapping systems based on machine vision targeting approximately 90% of weed patches (Fig. 18(d)). RHEA proposed two complementary UGV and UAV perception systems for real-time weed identification in wide-row crops detected by UGV and weed patch detection in narrow-row crops detected by remote sensing observed by UAV perception.

For pesticide spraying, Tourrette et al. (2018) proposed a spraying system based on UWB technology to control the formation of a mobile platform that follows a leader (Fig. 18(f)). The system allowed comparative localization of two mobile robots without visual communication and avoided the limitations of GPS when moving near a high tree canopy. The leader robot could move either autonomously or remotely. However, the advantages of parallel and limited spraying should mitigate the maneuverability of the sprayer in practical applications.

4.4. Irrigation

Irrigation in agriculture is becoming increasingly important owing to increasing global water shortages. It is difficult to estimate the condition of irrigation systems because of the need to monitor several factors, including the quality, amount, and location of water. Some irrigation applications require remote sensing over a wide area within a short time (Jimenez et al., 2020; Jiménez et al., 2022). Therefore, research is being actively conducted to measure water systems for irrigation by attaching sensors to UAVs. However, the acquisition of imagery on a geographic scale using a single UAV is difficult. Therefore, multiple UAVs are required to simultaneously measure large areas (Thayer et al., 2018).

Chao et al. (2008) designed a multiple UAVs system of cooperative remote sensing for real-time irrigation control and water management. Each UAV conveyed cameras with different wavelength bands. These cameras formed an array to perform multispectral imaging with bands that were reconfigurable, depending on the mission. In addition, a basic threshold filter was used to show the probability of using the NIR image to determine water coverage. The RGB and NIR images produced during the experiment are shown in Fig. 18(e).

4.5. Fertilization

Theoretically, fertilizer application to farms often increases crop yields; however, it is necessary to determine the ideal amount. Through remote sensing, spatially dense information that can contribute to fertilization management decisions or provide feedback can be gathered. There is a potential aim to predict the amount of fertilizer required to attain an ideal crop yield accurately without the excessive use of fertilizers, which can cause financial loss and pose environmental hazards. Some crops cannot be effectively fertilized because they grow rapidly. Therefore, the use of robots to ensure timely supply of fertilizer should be studied.

Minßen et al. (2011) studied a fertilizing system using a multirobot called *CareRowBot* (Fig. 18(g)). *CareRowBot* was designed to solve the fertilization problem by moving easily between corn rows and aiming the fertilizer directly at each plant. The authors then evaluated two types of fertilizer applications: an intense application with fixed dosage and an extended application with varying dosage. Experiments have shown that when applying *CareRowBot* to 150 ha, there is a cost of approximately 70 €/ha and that it would not be economically feasible, compared to the cost of approximately 30 €/ha when fertilizing using common approaches. The authors mentioned that more modular approaches must be included in the calculations to reduce operating costs.

4.6. Phenotyping

Crop data can be largely divided into genetic and phenotyping data, of which phenotyping is the most recent field of study. Phenotype is the observable appearance data of crops in reaction to the changing environment (Fonteijn et al., 2021; Jez et al., 2021; Atefi et al., 2021). One way to exploit phenotypes is using fruit color and shape to check whether the cultivation environment is pleasant or the fruit needs to be watered. Previously, crops were cultivated based on farmers' subjective judgment; however, the use of quantified raw data can increase crop productivity and quality to predicted levels more accurately.

In Gao et al. (2018a), lightweight distributed MRSs were proposed for obtaining the phenotypic data of row crops (Fig. 18(h)). The movement of the robots were based on an entropy-based informative path planning technique that incorporated a Gaussian model to obtain the desired positions of each robot in the field. The experiment results demonstrated that, when collecting data at different stages, the average estimated histogram error was inversely proportional to the number of iterations. Furthermore, the authors indicated a future plan to integrate the UAV with the MRS to realize multi-resolution phenotyping capabilities. Recently, multiple manipulator systems with deep learning-based planners for plant phenotyping have been developed (Wu et al., 2019). The planner uses a neural network to calculate the next-best viewpoints. However, the phenotyping performance significantly depends on the trained networks.

4.7. Harvesting

Harvesting is not only a physically tiring task; it also requires a large amount of skilled labor (Wang et al., 2022). Although the harvesting of some crops, such as rice and wheat, is well automated using tractors, other fruits and crops have not yet been actively roboticized (Roshanianfard et al., 2022; Kootstra et al., 2021; Park et al., 2021; Fue et al., 2020). The multirobot technology applied in harvesting can be divided into two types: multiple platforms cooperating on harvest (Johnson et al., 2009) and a single robot with multiple robot arms mounted on it to perform harvest together (Zion et al., 2014; Mann et al., 2016).

In the case of cooperation between multiple platforms, Iida et al. (2017) studied a cooperative harvesting system by combining two robots using wireless communication. The two robots worked together by communicating their location with each other and performing actions, such as reducing their speed when there is impending collision, while harvesting together. As Robot 2 approached Robot 1 (at a distance greater than 7.5 m) in the field experiment, it came to a halt, hence demonstrating successful cooperation and avoidance of collision between both robots during harvesting .

In the case of cooperation between multiple robot arms, Zhao et al. (2016) developed a modular concept that works based on human–robot collaboration (Vasconez et al., 2019; Benos et al., 2020; Anagnostis et al., 2021) of a dual-arm robot for harvesting (Fig. 18(i)). The system was tested to determine the adaptability and reliability of the dual-arm harvesting robot. Experiments proved that the robot could pick tomatoes on its own; once all the ripe fruits had been harvested, the operator moved the robot to the next workspace. However, camera observation of tomatoes may be ineffective under specific conditions.

5. Discussions and challenges

5.1. Commercialization

In this study, we reviewed the literature on the application of MRS in agriculture. Although MRSs have been extensively studied, it is still undergoing research and has not yet been commercialized. Therefore, its commercialization remains a challenge. To commercialize multirobots, they must be safe, economically feasible, technically capable of performing the intended task, and accepted by society and

growers (Bac et al., 2014). In other words, definitions, such as aesthetic, economic, social safety, ethical, and legal aspects, along with additional technical aspects, may be required. Setting technical and economic requirements requires complex interactions between variables, such as success rate, system cost, and cycle time. However, multirobot systems in agriculture are focused on improving system performance in unstructured environments. This approach may be slightly different from the commercialization point of view. Therefore, multirobot systems require a new perspective of control for commercialization.

In an unstructured and unknown agricultural environment, MRSs are more difficult to apply and commercialize. For example, harvesting robots have not yet become commercially available for fruit and vegetable harvesting (Bac et al., 2014). Moreover, multirobots are rarely commercialized and several difficulties exist. The difficulty of commercializing MRSs may be understood from the perspective of controlling a multi-harvesting robot. Unstructured environments require scalability, control, and accurate localization. Most researchers have focused on perception and planning to increase control accuracy; however, they have not considered scalability. Additionally, MRS studies have validated the possibility of improving production capacity, productivity, quality, and profitability through theory and simulation. However, the performance of MRSs in practical environments that exhibit real-time changes in response to external factors such as weather should be studied. This demonstration is an important factor in unstructured environments. It is still difficult to satisfy both scalability and control accuracy in a practical demonstration. Therefore, MRSs require continuous research and development. We discuss current and future research from the perspective of commercialization. This discussion contributes to MRS at the level of commercialization in the agricultural environment.

In MRSs, communication between robots is an effective interaction that can be complex, tacit, and explicit communication (Ismail et al., 2018). Therefore, major tractor manufacturers focus on communication between the MRSs. John Deere used its own communication system called JDLink to monitor the current status and condition of the machine, evaluate machine performance and efficiency, and make appropriate decisions. *JDLink* was developed to coordinate multiple platforms and operations in the field to share coverage maps and guides between robots to improve the logistics and efficiency of multiple robots operations. Fendt's *Optivisor* comprises two components: control and planning (Blender et al., 2016). The plan has initial execution settings that can be adjusted during the implementation of the task. The control ensures communication between the robots, supervision, fault handling, and communication with cloud servers. *CaseIH* uses wireless communications to synchronize the driving and operation of harvesting and grain-carting tractors. Once the grain cart enters the harvester and active area, the direction of the tractor, speed, and alignment can be controlled to support unloading during harvest (Thomasson et al., 2018). In these studies, the MRS was developed with focus on the communication between robots. However, human interaction cannot be overlooked for commercialization. To use the system efficiently in all situations, it is necessary to interact with the understanding of the environment and the heuristic experience of the operator. The commercialization of MRSs can be accelerated through an in-depth discussion on how to effectively interact with workers in the development stage.

Such effective interactions can be achieved by communicating with developers and operators on how to design user-friendly interfaces. As the number of robots increases, the increase in interfaces and communications makes the control of robots more complex and complicated. Most MRSs have high entry barriers that can only be controlled by experts. Furthermore, they do not guarantee robustness and certainty, and may, therefore, not work in unexpected situations. Thus, they should be visually identifiable and controlled by the user. For example, a graphical user interface (GUI) for controlling a multi-robot should be configured such that real operators in the field can easily use it. In agriculture, the GUI can be configured differently according to the environment and control method (Hong et al., 2017). A multirobot system can be built as a decentralized control system, and tasks can be performed automatically by selecting a mission and robot. However, users must understand and control each robot in real time using a centralized controller to handle large-scale environments more easily. Therefore, the MRS may need to be developed as a centralized control system from a commercial perspective.

5.2. Cooperative manipulation

Cooperative manipulation has been widely applied in object transportation studies. In Tuci et al. (2018), strong cooperative manipulation was classified according to strategy and divided into three types: pushing-only, grasping, and caging. Most researchers on cooperative manipulation in agriculture have focused on weak cooperation (Kim and Son, 2020; Kim et al., 2020a). In particular, weak cooperative manipulation in harvesting robots is being studied for individual robot control (Williams et al., 2019; Xiong et al., 2020). Although strong cooperation has not yet been researched in agriculture, it has high potential. Considerable research may make it usable in various applications.

In agriculture, strong cooperative manipulation can be utilized for harvesting and transporting objects, as shown in Fig. 19. For example, single-harvesting robots have limitations in harvesting because of the influence of surrounding obstacles such as canopies and pipes. These limitations can be overcome through cooperation between both manipulators. To harvest fruits manually, most people will hold the fruit with one hand and cut the stem with the other. Using this manual harvesting method, two manipulators can cooperate on harvesting (Zhao et al., 2016). Cooperative manipulation can increase the harvest success rate, which is lower than that of previous harvesting robots. However, this can also increase the cycle time, and, by extension, reduced performance. To use multiple manipulators, collision avoidance between robots through various measures, such as defining the workspace of each manipulator, motion planning, and path planning, must be considered. Each robot arm can be expected to shorten the overall working time when performing the work by moving along the optimal path.

A ground manipulator (GM) and aerial manipulator (AM) can be used to transport objects, and farming can be performed using GM + GM (Petitti et al., 2016), GM + AM (Staub et al., 2017), and AM + AM (Kim et al., 2018). For example, fruits that grow at relatively high heights can be damaged by people, when using ladder cars or climbing trees to harvest fruits. To overcome this issue, a camera is used to collect information on the position and pose of the crop, and the desired crop is harvested by controlling the position of the manipulator, which is mounted on the UAV. Moreover, it can be used for tasks such as pruning (You et al., 2020; Tinoco et al., 2021; Zahid et al., 2021). The combination of robots is determined based on the working environment. For example, in an environment surrounded by structures, it would be difficult to perform farming using a combination of AMs. Combinations of these heterogeneous multirobots are expected to improve system stability and scalability in unstructured environments.

5.3. Further applications in geoscience and life science

Numerous studies have been conducted to understand and monitor natural systems using a single robot to ensure efficient resource utilization while maintaining good crop health (Aguiar et al., 2020; Oliveira et al., 2021b). However, the range of nature is extremely wide to be monitored using a single robot with a limited monitoring range. Studies on geoscience consider wide and remote regions, thereby making it difficult to measure the effects of risks such as climate change or pollution. In addition, the change in the field environments is significant and the measured values exhibit a high deviation. Therefore, to effectively monitor a wide range of natural systems, multirobots can

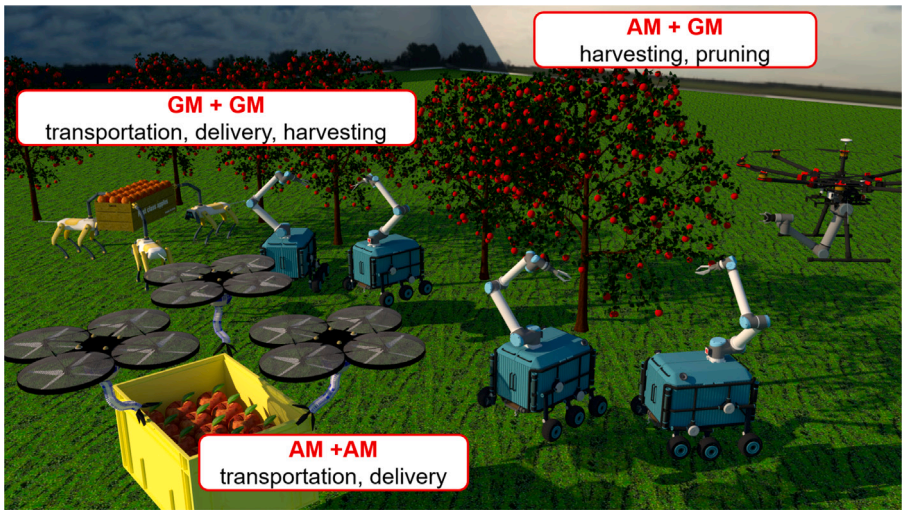


Fig. 19. Cooperative manipulation is applied to various multirobot applications.

be applied in life science and geoscience (Roldán-Gómez et al., 2021; Liu et al., 2021; Tian et al., 2020; Ebadi et al., 2020; Schuster et al., 2020).

Currently, MRS in geoscience is mostly applied to remote sensing and sampling. MRS-based remote sensing and sampling is being studied primarily for soil and water quality management. In Valada et al. (2014), dynamic spatial phenomena based on multiple autonomous surface crafts were monitored to determine the degree of contamination on the surface of water resources, and data were collected from large distributed areas. Among the factors affecting the biological activity of water, the level of contamination on the surface of water resources was investigated by sampling the water temperature and the salts dissolved therein. Soil sampling helps to determine the appropriate amount of nutrients, such as fertilizers, pesticides, and water, needed for the field. If the soil sampling area is wide, accurate information on the desired area can be collected using the MRS. In Deusdado et al. (2016), soil information was obtained through soil sampling by a team of UGV and UAV. The task and workspace were allocated to the UGV based on the aerial images obtained from the UAV. The UGV, which was attached to the manipulator, performed soil sampling in the assigned areas.

In life sciences, the conservation management of certain endangered species depends on understanding how these species interact with their environment (Cliff et al., 2018). An understanding of the environment is needed to solve various environmental issues, including how animals use habitats, animal migrations, and activities that cause diseases to spread among them. This would help identify the steps required to save endangered species.

Insects (e.g., bees) make pollination possible, which is essential for food production. In Lautenbach et al. (2012), it was calculated that humans benefit approximately $350 billion from pollination conducted by insects. Insects can bring about significant benefits; however, they are always at risk from natural enemies. Therefore, it is necessary to consider ways of protecting them without destroying the ecosystem. To protect insects, tracking and analyzing their behavior is an important issue. MRS has significant advantages because it can be used to track individual and multiple insects. In Berman et al. (2011), a heterogeneous MRS control policy was designed to track bees pollinating blueberry fields. To ensure scalability, each robot, controlled by a distributed controller makes decisions using only local information obtained through detection and communication, without knowledge of the global system status.

In Nguyen et al. (2019), Kim et al. (2019a), Ju and Son (2022), Kim et al. (2022), the authors introduced a UAV system that tracks and locates animals by measuring the received signal strength indicator value using radio tags attached to endangered species. Tracking using a single antenna has limited directivity and performance; therefore, the use of multiple antennas can prove to be more effective (Le et al., 2017). However, problems relating to the limited UAV payload arise when multiple antennas are installed. Therefore, multiple UAVs with installed antennas can be utilized to improve tracking performance. Furthermore, MRS can help minimize search time and solve the limited battery life problem observed in the case of a single UAV.

In addition, in many MRS studies, even if there is an obstacle between robots, absolute and global coordinates can be used to know the location of other robots. Current applications of MRS in the field of life sciences consider static and nondynamic obstacles. However, to perform a complete task, a robot must be able to respond actively to environmental variables. In the life sciences environment, there are too many static and dynamic obstacles and environmental variables in the model, and it is very difficult to model all of them. Therefore, MRS requires an approach other than modeling all the environmental variables. For example, a control strategy can be designed based on a system's disaster recovery capability and connectivity by modeling a scenario. Modeling mission scenarios can have significant advantages in understanding each robot's behavior during a mission and providing more appropriate support.

6. Conclusion

We reviewed agricultural robots and MRSs that need to be introduced and developed in the future. Compared with single-robot systems, MRSs offer increased work efficiency and convenience. Many issues need to be addressed for advanced automation and robotization. Specifically, a heterogeneous robot system consisting of a ground robot, aerial robot, and manipulator must be studied further for flexibility and scalability. In this study, we examined and comprehensively investigated state-of-the-art MRS for agricultural applications. Furthermore, future research and the problems to be dealt with in MRS are suggested in detail. MRS for agriculture, which is currently being actively developed, is summarized in this paper. A significant contribution of this study is the proposal of a standard that can be referenced in future studies and markets. The application potential of an agricultural robot system that solves the highlighted challenges and limitations and guarantees collaboration between homogeneous or heterogeneous robots in the field will be outstanding. Agricultural automation is expected to develop into a heterogeneous MRS capable of handling complex tasks.

CRediT authorship contribution statement

Chanyoung Ju: Conceptualization, Investigation, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Jeongeun Kim:** Conceptualization, Investigation, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Jaehwi Seol:** Conceptualization, Investigation, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Hyoung Il Son:** Writing – review & editing, Project administration, Funding acquisition, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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